Selected Topics in Product and Internet Marketing

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The Faculty of Business, Economics and Informatics of the University of Zurich hereby authorizes the printing of this dissertation, without indicating an opinion of the views expressed in the work.

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1 Introduction

1.1 Connection in Marketing

Business environment nowadays are complex in nature in the sense that market participants are closely connected. For companies, they meet each other in different markets; and for consumers, they link themselves to each other in various online platforms. Such feature requires more research attention to explore the implication of the connection among market participant: what is its effect on company performances; how does it affect consumer behaviors; and how itself can be influence by business and technology innovations. Understanding these issues is crucial for business successes. This dissertation explores these issues through three distinct papers. Specifically, we examine the phenomenon of brands coexisting with their siblings and competitors in multiple product markets and the effect of such overlap on brand performances; we analyze the business strategy in the coupon practice of linking consumers to each other through coupon trading and investigate whether it leads to higher coupon redemption; and we measure the extent to which virtual currency impacts platform users' individual behaviors and their interactions.

This dissertation highlights the importance of taking connection, dependency and influence among companies and those among consumers into consideration when doing research in marketing. It offers insights on evaluating and enhancing the performance of companies and the engagement of consumers through analyzing the effect, the application and the influential factor of such connection. The three independent papers in this dissertation are all empirical in nature. Using different statistical modeling strategies, they reveal the validity and usefulness of establishing connections among companies and that among consumers. Based on the empirical analyses, this dissertation delivers generalizable results and provides managerial implications to the existing marketing research and practices.

1.2 Overview of Studies in This Dissertation

This dissertation contributes to existing research in several ways: In the first study, the connection among brands and companies is analyzed from the angle of multimarket contact. Against the background of the mass adoption of multi-brand multi-market overlap, this work is the first in the existing marketing research to empirically measure and compare the effect of multimarket contact among sibling brands and competing brands. In the second study, the connection among consumers is analyzed in the coupon industry from the angle of coupon trading. Against the background of the booming in digital coupons and online coupon platforms, this work empirically investigates the effect of coupon trading on coupon redemption for the first time in marketing research. In the third study, the connection among consumers is further examined from the angle of testing virtual currency's effect on consumers' interaction. Against the background of the popularity of virtual currency, this work is the first in the marketing research to bridge the literature on money and that on virtual currency. For the first time, whether virtual currency can act as an influential factor on consumers' interaction in online environment is empirically investigated. A brief overview of the three studies constituting this dissertation is presented in Table 1.1. In the table, research questions, research contributions, research data and empirical methods are summarized.

Table 1.1 Overview of the thesis structure

Study 1: *Multimarket Contact with Sibling Brands*

Research questions	**Core contributions**	**Data basis**
Given imperfect observability, what is the competition deterrence effect of the multimarket contact with brands from the same company compared to the effect of the MMC with brands from different companies?	- Investigating not only the effect of MMC on competition behaviors among competing brands, but also among sibling brands. - Basing the analysis on the under-researched product market. - Applying both pooled and fixed effects quantile regression to avoid artificial censoring and to take into consideration the brand heterogeneity.	Monthly sales of 38 major brands from 17 automobile manufacturing companies in the U.S. market ranging from January 2009 to February 2012; brand characteristics; brands' multimarket contacts and market environment etc.

Empirical methods: Pooled and fixed effects quantile regression

Main results:
- MMC with competing brands functions effectively as a defection deterrence mechanism.
- There is no evidence indicates that MMC with sibling brands functions effectively as a defection deterrence mechanism.
- Market level MMC does not seem to affect brands‘ competition behavior.

Study 2: *The Social Exposure Effect of Coupon Trading on Coupon Redemption*

Research questions	**Core contributions**	**Data basis**
Does coupon trading increase coupon redemption likelihood within the context of digital coupons and third-party coupon platforms due to the repeated exposure towards product related information generated among consumers themselves?	- Extending the existing coupon literature by examining the effect of coupon trading on coupon redemption likelihood through the social exposure generated among consumers themselves. - Analyzing the effect of coupon trading on coupon redemption behavior based on a dataset with comprehensive consumer behavior. - Applying a cross-classified discrete time event history approach to capture the complex data structure and to derive robust results.	A longitudinal dataset ranging from January 2012 to December 2012 based on a Swiss online coupon service provider, with a sample size of 2,224,838 observations, including 32,603 consumers, 265 products, 1,923,405 coupon trades and 7,773 coupon redemptions.

Empirical methods: Cross-classified discrete time event history analysis

Main results:
- Coupon trading positively affects coupon redemption likelihood due to the repeated exposure towards product related information generated among consumers themselves.
- Coupon trading positively affects coupon redemption likelihood even when the coupons are not actually received by consumers.
- Rather than causing mental burden, there seems to be a positive spillover effect among trading activities on different products.

Study 3: *Two Sides of the Same Coin: The Effect of Virtual Currency on User Behavior*		
Research questions What is the effect of virtual currency on online platform users' behaviors? Does it properly function as an incentivizing power? Is there any potentially negative effect of virtual currency?	**Core contributions** - Extending the existing virtual currency literature by empirically measure the effect of virtual currency on online platform users' behaviors. - Bridging research on money and that on virtual currency by extending the findings on money psychology to the context of virtual currency. - Taking on a more balanced view of the effect of virtual currency by investigating its positive as well as negative effect.	**Data basis** Comprehensive user behavior data collected from a Swiss online platform over a time period of 47 weeks based on 16,962 platform users, 1,315,899 total logins, 711,256 trade proposals and 35,227 product redemptions.

Empirical methods: Fixed effects Poisson regression

Main results:
- Virtual currency, as an incentivizing force and as an instrument of payment, facilitates platform users in attaining their personal goal of product redemption.
- The demand for virtual currency drives users to log onto the platform significantly more often.
- Virtual currency decreases interaction among users.

1.2.1 Summary of Study One (Chapter 2)

In the first study, we attempt to compare the effect of multimarket contact with sibling brands and the effect of multimarket contact with competing brands, given imperfect observability. Multimarket contact (MMC) is broadly defined as a situation in which firms exist simultaneously with rivals in more than one market (Karnani & Wernerfelt, 1985). In the modern business environment, companies are commonly inter-connected in the sense that they meet each other in different product markets. It has long been argued that the outcome of such MMC is lower rivalry intensity among firms, a phenomenon known as mutual forbearance (Bernheim & Whinston, 1990; Edwards, 1955; Scott, 1991). This is because that with the existence of MMC, aggressive and competitive moves by a focal firm in one market can lead to retaliation from rivals in other markets in which the firms coexist. The term "sibling brands" is used to describe brands from the same company and "competing brands" for brands from different companies. Nowadays, companies often have multiple brands coexisting simultaneously in multiple markets. Whether there is a significant difference between the effect of MMC with sibling brands and that of MMC with competing brands can have a profound influence on the behavior of a focal brand, which affects the performance of the companies in turn. Imperfect observability indicates that competition moves may not always be perfectly observed. The rapidly changing business environment and the non-price competition in oligopolistic industries renders the full observability assumption implausible.

We analyze brand-level panel data from the U.S. automobile industry over 37 months using quantile regression. Our results suggest that while MMC with competing brands works effectively as a defection-deterrence mechanism. However, no evidence indicates that brands respond to MMC with siblings. This indicates that companies with multi-brand, multi-market overlap will not be at a competitive disadvantage compared to groups that do not adopt this strategy, hence validating such business practices. This study extends existing MMC literature and bridges MMC with brand strategy, offering important implications for researchers and practitioners.

1.2.2 Summary of Study Two (Chapter 3)

In the second study, we examine the social exposure effect of coupon trading on coupon redemption. Accompanying the surge in digital coupons, a handful number of online third-party coupon service providers have emerged due to the lucrative business opportunities and revenue gains (Kumar & Rajan, 2012). Coupon service providers heavily rely on coupon redemptions to generate revenues, to build up reputation, and to draw external investment. Thus, exploring ways to increase coupon redemption rate is very important for coupon service providers. With coupon trading, consumers are repeatedly exposed to product related information whenever other consumers suggest them for a trade. Different from FSI (Free

Standing Insert) or retailer customized coupons, where coupon manufacturers and coupon retailers are the source of influence, coupon trading affects coupon redemption due to the social exposure effect induced among consumers themselves. In this study, we measure the effect of coupon trading on coupon redemption likelihood through such social exposure.

The empirical analysis is built on a longitudinal dataset collected from a Swiss online coupon service provider. The data contains consumer and product information ranging from January 2012 to December 2012 for one full year and records 1,923,405 coupon trades, 32,603 consumers, 265 products and a total number of 7,773 redemptions. To capture temporal dependency, consumer heterogeneity and product heterogeneity, a cross-classified discrete time event history analysis is estimated by MCMC (Monte Carlo Markov Chain). Our results suggest that coupon trading can increase coupon redemption likelihood due to the consumer-induced exposure towards product related information. This implies that the positive effect of coupon trading leads to a higher propensity and shorter time period for coupon platforms to collect revenues, ceteris paribus. Our work provides important implications to both the academia and the industry.

1.2.3 Summary of Study Three (Chapter 4)

In the third study, we measure the effect of virtual currency on platform users' behaviors. To retain and motivate platform users, many practitioners are following the trend of introducing virtual currency on their platforms (Castronova, 2014). However, the underlying reasoning for such practice has mainly vaguely rooted in the traditional economic sense that virtual currency, due to its similarity to money in terms of the instrumentality, would make the market of exchange more liquid. Our results show that without fully understanding the effect of virtual currency, the implementation can lead to unsatisfactory result.

Research on money and money psychology has produced prolific results and has greatly advanced our understanding of the effect of money on people's behavior. Though gaining considerable popularity, virtual currency has received limited research attention compared to money. By empirically investigating both the positive effect and negative effect of virtual currency on platform users' behaviors, our work addresses the gaps in both the academia and the industry.

This study collects data from a Swiss online social gaming and shopping platform. The longitudinal data includes 16,962 platform users from late January 2013 to late December 2013 over a total length of 47 weeks. Using fixed effects Poisson regression, we find that virtual currency can indeed exert significant influence on platform users' behaviors. Specifically, our results suggest that (1) virtual currency facilitates platform users in attaining their personal goals as an incentivizing force and as an instrument of payment; (2) the demand for virtual currency retains platform users on the platform; (3) virtual currency undermines user interaction on average. The finding on the effect of virtual currency echoes previous research on money and testifies that, same as money, virtual currency incentivizes users, but only in terms of individualism. The results in this paper offer important implications and guidelines to the application of virtual currency

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2 Multimarket Contact with Sibling Brands

Abstract

Multimarket contact (MMC) plays an important role in modern business. Although MMC is an active research topic, studies have overlooked the dynamics among multimarket sibling brands. In this paper, we test the competition-deterrence effect of MMC with sibling brands and with competing brands. Unlike most of the existing literature, which has assumed full observability, we base our analysis within the framework of imperfect observability. We analyze brand-level panel data from the U.S. automobile industry over 37 months. Our results suggest that while MMC with competing brands works effectively as a defection-deterrence mechanism, no evidence indicates that brands respond to MMC with siblings. This study extends existing MMC literature and bridges MMC with brand strategy, offering important implications for researchers and practitioners.

Keywords: multimarket contact, imperfect observability, multi-brand strategy, multi-market strategy, quantile regression

2.1 Introduction

In the modern business environment, companies commonly operate in different product markets, which drive the emergence of multimarket contact (MMC). MMC is broadly defined as a situation in which firms exist simultaneously with rivals in more than one market (Karnani & Wernerfelt, 1985). With the existence of MMC, aggressive and competitive moves by a focal firm in one market can lead to retaliation from rivals in other markets in which the firms coexist. It has long been argued that the outcome of MMC is lower rivalry intensity among firms, a phenomenon known as mutual forbearance (Bernheim & Whinston, 1990; Edwards, 1955; Scott, 1991).

While considerable research has focused on the topic of MMC, two issues require additional research attention. First, MMC models usually assume full observability, where defections from equilibrium (violations of mutual forbearance) can always be detected and punished (Yu & Cannella, 2013). However, competition moves may not always be perfectly observed. This partial observability may be the result of the currently rapidly changing business environment in the sense that competitive actions have extended well beyond the domain of prices. It is difficult for competitors to perfectly monitor non-price competition moves, such as services. In many oligopolistic industries, such as the automobile industry, non-price competition is the major source of rivalry due to the fear of price wars (Rios, McConnell, & Brue, 2013). Compared to price competition, non-price competition is difficult to evaluate; hence, full observability is rendered implausible.

Second, companies often have multiple brands (referred to as sibling brands in this paper, in contrast with competing brands, which are brands from different companies) coexisting simultaneously in multiple markets. Whether there is a significant difference between the effect of MMC with sibling brands and that of MMC with competing brands can have a profound influence on the behavior of a focal brand, which affects the performance of the companies in turn. Thus, investigating the effect of MMC at the brand level is of both theoretic and practical importance, especially for firms that simultaneously offer products under several brands in various markets. Studies based on aggregated firm levels automatically assume multi-brand companies as unitary market participants and ignore competition at the brand level. Although this approach is frequently adopted, such an analysis is less than ideal in the modern business environment.

Therefore, the two above-mentioned issues are of crucial importance to both academia and the industry. For this reason, we attempt to answer the following research question: given imperfect observability, what is the effect of the MMC of several brands from the same company compared to the effect of the MMC with brands from different companies? By answering this research question, we are able to extend existing MMC studies and contribute to this stream of literature by addressing the earlier-mentioned research gaps. We use the term “sibling brands” to describe brands from the same company and “competing brands” for brands from different companies. Similar to previous studies, the authors do not assume perfect observability (Greve, 2008).

In this study, the empirical models are based on the automobile industry during the most recent crisis in North America. This specific time window is interesting to study because the whole industry is under pressure, which offers a new context in which to study MMC and competition. Good knowledge on brand performance under MMC can thus help brands and companies or manufacturing groups lay a solid foundation for future prosperity[1]. We investigate the effect of MMC on brand performance in product markets by applying the quantile regression method. It has long been argued that MMC can decrease market share instability (Heggestad & Rhoades, 1978). Hence, the variation in sales growth conditional on MMC is expected to be heterogeneous across the distribution of sales growth. Due to the

[1] In the automobile industry, multi-brand companies are often referred to as manufacturing groups. Thus, companies and manufacturing groups are used interchangeably in the rest of this paper.

potential unequal variance in sales growth, we argue that quantile regression is the more appropriate and robust method with which to study our research question and derive inferences from the empirical model. It enables us to obtain results across different segments of sales growth while being robust to outliers.

In this paper, we show several important results. First, the results derived in this paper suggest that only the MMC with competing brands effectively serves as a defection-deterrence mechanism in the sense that it lowers the competition level and induces mutual forbearance. We do not find evidence that MMC with siblings facilitates mutual forbearance and competition deterrence. Second, our findings provide important managerial implications in the sense that the multi-brand, multi-market overlap business strategy is validated because MMC with siblings does not lead to a brand competing less intensively than brands without MMC with siblings. Therefore, companies or manufacturing groups with multi-brand, multi-market overlap will not be at a competitive disadvantage compared to groups that do not adopt this strategy. Specifically, for a manufacturing group that does not have multi-brand, multi-market overlap, as the MMC of its brands increases, the group competes less intensively in general; for a manufacturing group that adopts multi-brand, multi-market overlap by extending brands in multiple markets, the rules of the game change in such a sense that an increase in the overall MMC of its brands does not necessarily lower the group's competitive intensity because MMC with siblings does not deter competition. Groups that employ this strategy do not need to worry about losing competitive ground to competitors due to the additional mutual forbearance resulting from MMC among sibling brands.

2.2 Related Literature and Theoretical Framework

MMC has been studied across various industries, such as the airline industry

(Gimeno & Woo, 1999; Korn & Baum, 1999; Prince & Simon, 2009), financial industry (Greve, 2006; Hannan & Prager, 2009; Shipilov, 2009), health care industry (Shankar, 1999; Stephan *et al.*, 2003), and PC-related industries (Kang, Bayus, & Balasubramanian, 2010; Young *et al.*, 2000). Nevertheless, as one of the largest industries in the world, the automobile industry has not received much research attention regarding the topic of MMC. To the best of our knowledge, very limited research has been conducted in the automobile industry (Leheyda, 2008; Yu & Cannella, 2007). This paper enriches the diversification of the existing MMC literature by conducting empirical analyses on brands under single- and multi-brand automobile manufacturing groups.

MMC occurs when firms meet their competitors in multiple markets. With such frequent encounters, firms mutually recognize that their decisions are interdependent, which leads to lower competition intensity, a term known as “mutual forbearance”. The motivating logic is that firms are aware of the fact that their competitive moves in one market may provoke retaliation in all markets in which they coexist with their rivals (Evans & Kessides, 1994; Haveman & Nonnemaker, 2000; Heggestad & Rhoades, 1978). This means that when defection is always detected and punished, more MMC leads to more severe retaliation from rivals, who can respond to the defection in more markets. Therefore, under full observability, high MMC lowers competition intensity because it implies greater punishment strength (Bernheim & Whinston, 1990).

Most of the existing MMC literature assumes perfect monitoring in which any deviation from the collusive equilibrium is always detected and punished. However, given modern business practices, it is very difficult to perfectly monitor all competitors’ moves. Difficulty and costliness prevent the perfect observation of frequent price changes, especially in shorter time windows (e.g., monthly). Moreover, business practices such as non-price competition through services are not easy to evaluate, and these moves, with a stealthy nature and an ambiguous interpretation, pose great difficulty to full observation and are less likely to draw a response (Chen & Hambrick, 1995). This is especially true for oligopolistic markets such as the automobile industry because non-price competition is a major source of rivalry in such markets. While the existing literature on MMC relies mainly on the full observability assumption, imperfect monitoring requires additional research efforts because it is based on a different mechanism, namely, whether defection is detected. This mechanism contradicts the mechanism of mutual forbearance under full observability, which is based instead on whether sufficient punishments exist to deter defection. Full observability has been theoretically challenged as a necessary prerequisite to sustain mutual forbearance (Matsushima, 2001). However, empirical analyses of MMC under imperfect observability are scarce. Imperfect observability renders price analysis infeasible. By relying on sales growth instead of price to explore the effect of MMC, Greve (2008) showed that mutual forbearance could be sustained, even without full observability, and extended Matsushima's theoretical two-player repeated games model into an empirical model with multiple non-identical firms. Due to imperfect observability, firms cannot fully monitor competitors' moves. Rather, they can only imperfectly monitor competitors through the realization of some noisy signal (e.g., sales growth). Because the market is noisy (e.g., random sales growth variation due to some demand shocks), the signal is triggered in defection markets with positive probability p_d<1 and in non-defection markets with positive probability p_n<p_d.

Firms can individually detect defection if the number of markets in which the signal is observed reaches some threshold r set by the firms. Therefore, as firms overlap with each other more, the likelihood they will observe the signal increases (i.e., the likelihood that the threshold r will be reached increases), meaning a higher probability to detect defection. Moreover, firms can also learn that someone has defected by observing other players initiating punishments after discovering the defection. This notion is illustrated in Figure 2.1.

Firm	Market 1	2	3	4	5
A	X	X	X	X	X
B	X		X		
C	X	X			
D	X		X		
E	X	X			
F	X				
G	X				
H	X				
I		X			X
J		X			
K			X		X
L			X		
M				X	
N			X		X
Multimarket Contact					
Firm A	4	3	4	0	3
Market Level	5/8	4/5	5/6	0/2	4/4

Figure 2.1 Firm-level MMC and market-level MMC

Firms A and B coexist in two markets (markets 1 and 3). If firm A defects in three out of the five markets in which it operates (e.g., in markets 2, 3 and 4), the probability that its defection is detected will be higher if another firm C has MMC with firm A (e.g., in markets 1 and 2). The reason for this result is, first, that firm B and C cover more markets in which the defection signal can be potentially observed, increasing the overall probability that A's defection is detected. Second, once B or C is sure of the defection and begins to retaliate, for example, in market 1, the other company (B or C) can also learn that A has defected. Therefore, an increase in MMC enhances the probability that the defection is discovered. Even if the individual probability of detecting the defection is low, the joint probability can be sufficiently high when the defecting player has higher MMC. Therefore, Greve (2008) argued that as the amount of MMC a focal firm has increases, the probability that its defection will be detected increases, which, in turn, precipitates the firm to be reluctant to defect out of fear of being discovered. In line with previous research, we expect that MMC among competing brands lowers their incentive to defect:

H1: As a brand's MMC with competing brands in a focal market increases, its sales growth in this market decreases.

Extending the above argument further, as firms have fewer incentives to defect if they have MMC, given the same total number of players in the market, the market in which higher numbers of firms have MMC shall ensure a higher overall tacit collusion level. A higher collusion level means that the likelihood of undercutting other players is abundant. Consequently, it is lucrative for a player to defect in such a market. However, the argument in this study is slightly different from the argument in previous literature. While Greve (2008) stated that the sheer number of firms with MMC increases the potential collusion level, we argue that a ratio measure is more appropriate. Even with a high number of firms with MMC, a market can still have a lower collusion level if it is large enough to also embrace a non-negligible number of firms that have only single market contacts. Firms without MMC are not subjected to the competition deterrence that results from MMC. Their existence may increase the overall competition level, and their counterparties may be unwilling to raise the collusion level out of fear of being undercut. As a result, the potential gain from defection can be low in such markets because the collusion level, if it exists, may be low enough to resemble a competitive market. As illustrated in Figure 2.1, for Firm A, market 1 has higher number of firms with MMC than market 5. However, market 5 remains a more promising place for defection, as all the firms have MMC, which indicates a higher potential collusion level, and Firm A has fewer MMCs in that market. Thus, we hypothesize the following:

H2: As the market level of MMC increases, the brand's sales growth in the same market increases.

In this study, we also extend previous work by testing both the effect of MMC with sibling brands and the effect of MMC with competing brands. Although several studies have taken subsidiary-level factors into consideration, MMC with siblings was not modeled explicitly (Greve & Baum, 2001; Sengul & Gimeno, 2013; Yu *et al.*, 2009) due to data availability constraints. However, as we introduced previously, the widely adopted multi-brand strategy requires research effort to broaden the understanding of MMC and to expand our knowledge by taking into consideration the MMCs of sibling brands, as they can affect the brand-level and the company/manufacturing group-level performance. When brands' total MMC considers that of siblings, brands' response to the total MMC might differ from their response when the MMC does not involve siblings. MMC with siblings changes brands' response by offering different motives and incentives than MMC with competing brands, which we will explain in detail in the following paragraphs. The automobile industry provides a well-fitting context for the focus of this research, as a handful of automobile manufacturing groups operate multiple brands that overlap in multiple product markets.

Understanding the potential difference brands' behaviors when facing MMC with siblings and MMC with competing brands can offer important managerial implications for manufacturing groups. In order to study the effect of MMC with sibling brands, we must first recognize its differences from the MMC with competing brands, especially for multi-brand groups. While mutual forbearance among competitors can lower competition intensity and raise profit levels, it can also lead to inefficient relationships and erode competitive edge in the long run (Greve, 2008; Yu & Cannella, 2013). Therefore, it is critical for companies or manufacturing groups to consider their intra-group competition relationship. Groups may prefer or even induce intra-group competition to fend off competitors because it fosters efficiency and competitive edge (Fauli-Oller & Giralt, 1995; Phelps & Fuller, 2000). Moreover, groups may want to avoid coalitions among sibling brands that are not in the best interest of the group (Palmer, Jennings, & Zhou, 1993). Mutual forbearance resulting from MMC among sibling brands can breed inefficiency in competition and form coalitions with inertia to strive for better performance. However, it is evident that groups will tolerate or induce intra-group competition only up to the point that the group benefits from the competition.

Now, let us consider brands from a multi-brand group. If these brands initiate mutual forbearance in the market strictly based on the total detection probability, they would have to give up more sales growth opportunities at the same level of MMC with competing brands than brands without siblings because the additional MMC with sibling brands increases detection probability. From brands' point of view, this scenario is definitely not optimal. Obviously, competition is inevitable because sibling brands all have to fight for limited group resources and internal and external customers (Luo, 2005; Schmid & Schurig, 2003). Better-performing brands will be favored when allocating group resources. Consequently, brands with siblings will experience more intra-group rivalry pressure than brands without siblings, due to resource allocation or group-induced rivalry. Foregoing sales growth opportunities can put them at a disadvantage in intra-group competition. Moreover, managers may be less worried about being detected by siblings than about being caught by competing brands because, even if the defection is detected by siblings and results in full competition (because other brands can join the punishment if they observe retaliation), the resulting full competition will not lead to any benefits in the group, which the group surely does not want. The managers of the defecting brands can easily "pass the buck" to their peers from brands that initiated the retaliation from a total group loss point of view. Taking this reality into consideration, the siblings would not be as willing as competing brands to initiate retaliation upon detecting the defection. Therefore, it is natural to suspect that, as a mechanism to deter defection, the MMC with sibling brands will not work as effectively as MMC with competing brands. We therefore hypothesize the following:

H3: The effect of MMC with sibling brands on defection deterrence is not as effective as that of MMC with competing brands.

To the best of our knowledge, the authors are unaware of any previous research that specifically addresses this gap in the existing MMC literature. Kalnins's work (2004) is related to this topic, but with a different research focus. This obvious inadequacy has recently been noted and has led to a call for additional studies on within-firm MMC (Yu & Cannella, 2013).

In this paper, the authors focus on product markets rather than geographical markets. The unbalanced number of MMC studies using geographical markets and product markets calls for more attention to the latter setup (Greve, 2008). Because brands are nested in manufacturing groups, the results of a brand-level model based on product markets can be naturally extended to infer the performance at the group level and to facilitate interpretation. We provide a detailed discussion of this issue in the implication section.

2.3 Data and Methodology

To study MMC and rivalry among sibling brands, we focus on a single, major industry – the U.S. automobile industry. The automobile industry was chosen because the topic of this study is inherent in this particular industry and because of the industry's importance: it accounts for five percent of the U.S. GDP (Ramey & Vine, 2006). In the industry, automobile giants, commonly known as manufacturing groups, compose a significant portion (almost 95%) of the industry sales. Automobile groups usually operate a portfolio of brands, which can also overlap across different product markets. A major reason to follow this multi-brand strategy is that it offers automobile groups an effective way to segment the current highly competitive and diverse market in order to inhibit competitors from gaining a market share (Mason & Milne, 1994). Specifically, we construct a dataset of 38 major brands from 17 manufacturing groups, of which 34 brands were operated by 11 multi-brand automobile groups, between January 2009 and February 2012, for a sample of 4,829 observations after excluding the first observation period due to the lagged MMC measures. The list of brands and groups in this study is presented in Table 2.1. In Table 2.2, we show the summary statistics and correlation among covariates.

To capture the defection, we use the sales growth deviation (*SalesDev*) as the dependent variable in our empirical analysis. Following previous literature, we define sales growth deviation as the difference between the focal brand's sales growth and the median of all brands' growth in that market (Greve, 2008). Theoretically, if all players engage in mutual forbearance, they will all have homogenous sales growth, as no player attempts to grab shares from others. If some players defect, the defecting players will have higher sales growth, which positively deviates from the market median. The cooperating players, on the other hand, will not deviate from the market median. However, in reality, random variation in sales is inevitable. As a result, stochastic deviation from the market median can occur even if the focal brand does not defect. Nevertheless, the stochastic variation will not induce sales growth to deviate considerably from the market median. Only defection would lead to larger positive sales growth deviation, which will lead to evident skewness in the dependent variable, as large deviations are most likely to be positive (i.e., defection) and small deviations are close to 0 (i.e., stochastic variation). Our data also exhibit this feature with positive skewness and a large amount of small deviations clustered around 0. Thus, our data fit the theory and are appropriate for the intended statistical tests.

Table 2.1 List of automobile brands and groups

Company/Manufacturing Group	Brand
BMW	BMW
	MINI
FCA	CHRYSLER
	DODGE
	FIAT
	JEEP
	RAM
DAIMLER	MERCEDES-BENZ
	SMART
FORD	FORD
	LINCOLN
	MERCURY
	VOLVO (End in 2010)
GENERAL MOTORS	BUICK
	CADILLAC
	CHEVROLET
	GMC
	PONTIAC
	SAAB (End in 2010)
	SATURN
HONDA	ACURA
	HONDA
HYUNDAI	HYUNDAI
	KIA
MAZDA	MAZDA
MITSUBISHI	MITSUBISHI
NISSAN	INFINITI
	NISSAN
SAAB	SAAB (Since 2010)
SUBARU	SUBARU
SUZUKI	SUZUKI
TATA	JAGUAR
	LAND ROVER
TOYOTA	LEXUS
	SCION
	TOYOTA
VOLKSWAGEN	AUDI
	PORSCHE
	VOLKSWAGEN
VOLVO	VOLVO (Since 2010)

Table 2: Summary statistics and correlation table

Variable	Mean	SD	SalesDev	MarketGrowth	Single	HHI	Foreign	MarketShare	SibMMC	CompMMC
SalesDev	0.04399	0.381756								
MarketGrowth	0.03434	0.197356	0.0032							
Single	0.04017	0.196387	0.0005	0.0016						
HHI	0.13337	0.067063	-0.0041	-0.0059	-0.0720					
Foreign	11.07227	4.995063	-0.0264	0.0024	0.0528	-0.8231				
MarketShare	0.06882	0.081454	-0.0814	-0.0082	-0.1094	0.4111	-0.3552			
SibMMC	0.73017	0.877951	-0.0104	0.0084	-0.1702	-0.1632	0.1785	-0.0887		
CompMMC	12.66101	5.496743	-0.0169	0.0020	-0.4701	-0.6166	0.6871	-0.1783	0.2422	
MarketMMC	0.95950	0.061480	0.0134	-0.0084	-0.3086	0.2327	-0.1717	0.0719	0.1073	0.1832

Both industry reports and academic papers reach the consensus that automobile product segments constitute distinct markets (Leheyda, 2008; Requena-Silvente & Walker, 2005). Following Requena-Silvente and Walker (2005) and Leheyda (2008), we define markets based on the following product segments: small cars, mid-sized cars, large cars, luxury cars, sports cars, cross utility vehicles, sport utility vehicles, vans and pickups. This classification of the product market is also largely coherent with the practice of industrial organizations, such as the National Automobile Dealers Association (NADA). The dependent variable is derived based on monthly car sales data provided by Wards Automobile.

To test mutual forbearance, we include three MMC measures in our model:

- *SibMMC:* this measure accounts for the MMC that a brand has with its sibling brands, operationalized as the number of siblings in that market that have MMC with the focal brand.
- *CompMMC:* this measure accounts for the MMC that a brand has with its competing brands, operationalized as the number of competing brands in that market that have MMC with the focal brand.
- *MarketMMC:* this measure accounts for the potential gain if a focal player defects, operationalized as the ratio of the number of brands with at least one MMC in the market to the total number of brands in the market.

As a simple example, suppose brands A, D and E are from the same manufacturing group. In Figure 2.1, brand A has 4 MMCs in market 1 because brands B, C, D and E all coexist with brand A in markets other than market 1. Brands D and E are sibling brands of brand A; thus, brand A's *SibMMC* is 2. Brands B and C are competing brands of brand A; thus, brand A's *CompMMC* is 2. Among all eight brands in market 1, five have at least one MMC (i.e., brands A, B, C, D and E); thus, the market level *MarketMMC* is 5/8.

The coefficient and significance of *SibMMC* enables us to examine the effect of MMC with sibling brands on defection deterrence. Compared to the coefficient and significance of *CompMMC*, the results can show whether the *SibMMC* is more or less effective. For two reasons, we use a ratio measure for market-level MMC instead of a simple count for two reasons. First, as we already explained in the earlier section, the room left for a player to undercut fellow market participants depends on both the number of brands with MMC and the number without MMC. Thus, a ratio measure better captures the potential level of collusion in the market. Second, the ratio measure is used to reduce multicollinearity. All three measures are count based. Though a number of different operationalizations of MMC have been introduced in previous studies, we argue that in our context, count-based measures best fit our research setting. When competitive moves are not perfectly observed, the high probability of being discovered, i.e., the sufficiently large number of other brands with MMC with the focal brand, prevents the brand from defecting, as we explained previously.

In line with prior research, we use several additional variables to control market characteristics in our model. It is easier to coordinate behaviors in more concentrated markets. Thus, the Herfindahl Index (*HHI*) is introduced to separate the effect of MMC from market concentration, which serves as an alternative explanation of the uniform market behaviors of brands. Market participants are more tempted to plunder additional shares in growing markets. Foreign automakers have been argued to have superior cost structures than the domestic automakers. The competition level in the market can be higher with an increase in the number of foreign players. Thus, market growth (*MarketGrowth*) and numbers of foreign brands (*Foreign*) in the market are both included in the model. Smaller brands have lower stakes in maintaining tacit collusion. Single-market brands are arguably not subject to the competition deterrence mechanism of MMC. Hence, in the model, we also include market shares (*MarketShare*) and an indicator of whether a brand operates only in a single market

(*Single*) as brand-level control variables. Time fixed effects are modeled by including time dummies. The amount of monthly dummies would consume considerable degrees of freedom. Moreover, the month-by-month variation in time fixed effects is largely insignificant. Thus, we group the time fixed effects and estimate the models with quarterly dummies.

Following the logic that we presented in the last section, large positive sales growth deviation from the market median is a clear sign of defection, while small positive/negative deviation from the median can be simply stochastic variation. This logic indicates the need for a modeling strategy that can separate positive and negative deviation (because negative deviation is stochastic variation) and capture the non-central location of the dependent variable's conditional distribution (because only large positive deviation is a clear sign of defection). The previous literature has suggested artificially censoring sales growth deviation at 0 and using the Tobit estimator (Greve, 2008). However, censoring can be very costly because heteroscedasticity and non-normality can result in non-robustness and inconsistency in the Tobit estimator (Wooldridge, 2010). Heavy-tailed distribution is not uncommon in social phenomena and is surely the case for sales growth deviation. Therefore, we use quantile regression as the modeling methodology. Since the seminal work of Koenker and Bassett, the knowledge on quantile regression has been growing at a steady pace (Koenker, 2005; Koenker & Bassett, 1978). Using quantile regression does not require left-censoring the data and thus does not induce additional assumptions. Because quantiles $q >= 0.5$ correspond to the median and positive deviation from the median, we can effectively avoid artificially censoring the data by using quantile regression on quantiles $q >= 0.5$.

Moreover, our research interest lies more in the non-central location of the dependent variable's conditional distribution (i.e., larger positive deviation from the market median). Traditionally, researchers have extensively used models within the conditional mean framework. Nevertheless, conditional mean modeling has several inherent limitations (Hao & Naiman, 2007). While focusing on the central location, conditional mean models cannot reveal the effect of outcomes and covariates at non-central locations, and important distributional properties are ignored. In our case, however, the upper half of the sales growth deviation (positive deviation from the market median) is exactly where our interest lies (because the sales growth deviation is operationalized as the difference from the median). More specifically, the larger positive deviation at the tail of its distribution (i.e., the higher percentiles of sales growth) is even more valuable, as it is a clear sign of defection rather than small positive deviation attributable to stochastic variation. We therefore use quantile regression instead of a Tobit model in this study because it can appropriately capture the phenomenon of interest (i.e., the larger positive deviation of sales growth). Moreover, unlike conditional mean models, quantile regression is robust to outliers.

Another non-trivial issue with Tobit models relates to their inherent features. A Tobit model for positive sales growth deviation is based on both the probability that the deviation is positive and the conditional expected value of the positive deviation. More crucially, a Tobit model implicitly assumes that the process generating this information is the same, meaning that it is impossible to have cases with a lower probability of positive sales growth deviation but a larger magnitude of deviation when positive deviation occurs. Thus, a Tobit model can be restrictive and should be used with caution (Lin & Schmidt, 1984). Given all the above reasons, quantile regression with bootstrapped standard errors is a more robust modeling strategy in this case.

As a pre-analysis check on the variance components, we investigate a potential multilevel structure of the null model (Rabe-Hesketh & Skrondal, 2008). In Table 2.3, we compare the variance components of different specifications. None of the test statistics indicates the superiority of a multilevel model over pooling.

Table 2.2 Variance component analysis

	Compare to pooling
Observations nested in brands	(Prob > chi2) = 1
Observations nested in markets	(Prob > chi2) = 0.153
Observation nested in groups	(Prob > chi2) = 1
Cross-classified between brands and markets	(Prob > chi2) = 0.5915

Thus, our baseline model for the pth quantile is the following:[2]

$$SalesDev^{(p)} = \beta_0^{(p)} + \beta_1^{(p)}MarketGrowth + \beta_2^{(p)}HHI + \beta_3^{(p)}Foreign + \beta_4^{(p)}Single + \beta_5^{(p)}MarketShare + \beta_6^{(p)}SibMMC + \beta_7^{(p)}CompMMC + \beta_8^{(p)}MarketMMC + \sum_{j=9}^{20}\beta_j^{(p)}TimeDummy + \varepsilon^{(p)}$$

In addition to the baseline model, we run a quantile regression model with brand fixed effects to control for unobserved brand heterogeneity. The use of a fixed effects model introduces a dilemma in our study. On one hand, pooling can dampen the credibility of the model with potential omitted variable bias and endogeneity. On the other hand, while fixed effects greatly reduce the risk of omitted variable bias and endogeneity, they can eliminate many signals in the data and lead to substantially larger standard errors and p-values, especially when the variables of interest have little within-unit variation. Hence, we do not limit the interpretation of the results solely to the pooled model or to the fixed effects model. The estimation procedure for the fixed effects quantile regression model follows the work of Canay using a two-step estimator (Canay, 2011).[3] The standard "within" estimator is used in the first step to extract the fixed effects from the conditional mean model. The dependent variable is transformed in the second step by subtracting the fixed effects. The quantile regression estimation is then conducted on the transformed dependent variable. Bootstrapped standard errors are used for both the baseline model and the fixed effects model.

[2] Following constructs in the previous literature, the MMC variables and the market are temporally lagged.
[3] The pooled model is estimated using Stata 12. The fixed effects model is estimated based on Canay's R code "QRPanel," which is available on the author's web page. We adapt the code to accommodate the unbalanced panel structure in our data.

2.4 Results

In this section, we present the results of the quantile regression. Because our interest lies in defection, (i.e., positive sales growth deviation, which is defined as the growth higher than the median growth in a market), especially large deviation, we estimate the model for the following 10 quantiles of the data: 0.5, 0.55, 0.6, 0.65, 0.7, 0.75, 0.8, 0.85, 0.9, and 0.95. Instead of the asymptotic standard errors, we bootstrap the residuals with 1000 replications. According to Efron & Tibshirani (1994), 1,000 bootstrap replications are sufficient enough for robust inference of parameters, standard errors and confidence intervals.[4]

We show the results of the quantile regressions in Table 2.4 and 2.5. Model 1 is the pooled quantile regression, while Model 2 is the quantile regression with brand fixed effects. As the results suggest, the defection deterrence effect of MMC with competing brands is evident in the upper quantiles. It is obvious that the magnitude of the association between the positive sales growth deviation and MMC with competing brands varies significantly across different quantiles. The results from the two models are largely coherent. The effect of MMC with competing brands becomes significant beginning in the 80th percentile of the sales growth deviation in the pooled model, while it becomes significant beginning in the 85th percentile in the fixed effects model. The association increases steadily from the 85th percentile to the 95th percentile in both models, with effect sizes ranging from around 0.9% to more than 2% decrease in sales deviation. This suggests that MMC with competing brands works effectively as a defection deterrence mechanism only when the positive deviation of sales growth is larger in magnitude, which is understandable because small positive deviation

[4] We also run random effects and fixed effects Tobit models, following previous literature (Greve 2008). None of the MMC variables is statistically significant in either of the models. Because Tobit models inherently induce implausible assumptions, we do not report the results here. Detailed estimation results are available upon request.

Table 2.3 Pooled quantile regression

	Model 1									
Quantile	50	55	60	65	70	75	80	85	90	95
MarketGrowth	-0.001128	-0.003199	-0.001538	0.020817	0.032579	0.079094 ***	0.107807 ***	0.116827 ***	0.169185 ***	0.298555 ***
	(0.008801)	(0.012611)	(0.018617)	(0.023454)	(0.023069)	(0.026850)	(0.031118)	(0.041747)	(0.049909)	(0.093434)
HHI	0.011243	-0.012941	-0.073860	-0.100702	-0.195976	-0.151467	-0.188538	-0.072592	-0.219082	0.339771
	(0.040954)	(0.056934)	(0.084788)	(0.105750)	(0.119630)	(0.147654)	(0.189656)	(0.217303)	(0.267360)	(0.503232)
Foreign	-0.000534	-0.001587	-0.000960	-0.001905	-0.001432	-0.001158	-0.002486	-0.000109	-0.001868	-0.000527
	(0.000785)	(0.001161)	(0.001561)	(0.001806)	(0.001651)	(0.001968)	(0.002522)	(0.003083)	(0.004240)	(0.007093)
Single	-0.008610	-0.001940	-0.030758	-0.021722	-0.045851	-0.066470 **	-0.076270 *	-0.117132 **	-0.111912	0.016638
	(0.015728)	(0.019172)	(0.023359)	(0.030098)	(0.031100)	(0.032619)	(0.043539)	(0.059614)	(0.073128)	(0.203215)
MarketShare	-0.046713 *	-0.095223 ***	-0.122511 ***	-0.184264 ***	-0.242894 ***	-0.304501 ***	-0.425158 ***	-0.613012 ***	-0.804106 ***	-1.558880 ***
	(0.028172)	(0.031147)	(0.033253)	(0.041346)	(0.043968)	(0.053738)	(0.064861)	(0.072144)	(0.102408)	(0.216102)
SibMMC	-0.000775	0.000351	-0.000654	0.000833	-0.000961	0.002637	0.005389	0.004825	0.005237	0.003658
	(0.002089)	(0.002940)	(0.003923)	(0.004457)	(0.004722)	(0.005461)	(0.006360)	(0.007694)	(0.009573)	(0.016221)
CompMMC	0.000577	0.001406	-0.000025	0.000114	-0.001753	-0.002948 *	-0.004677 **	-0.008857 ***	-0.012935 ***	-0.020820 ***
	(0.000846)	(0.001079)	(0.001399)	(0.001688)	(0.001702)	(0.001689)	(0.002081)	(0.002731)	(0.003758)	(0.006202)
MarketMMC	-0.015747	-0.022774	0.002808	0.029898	0.060184	0.070243	0.148090	0.300268 **	0.439810 **	0.640769 **
	(0.032753)	(0.045895)	(0.058248)	(0.069803)	(0.073915)	(0.081767)	(0.105933)	(0.127153)	(0.175074)	(0.275708)

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 2.4 Brand fixed effects quantile regression

	Model 2									
Quantile	50	55	60	65	70	75	80	85	90	95
MarketGrowth	-0.005659	-0.005423	0.005098	0.031538	0.046346	0.077139 *	0.105027 **	0.116773 *	0.156610 **	0.263180 **
	(0.024332)	(0.02538)	(0.029576)	(0.036401)	(0.040429)	(0.043266)	(0.050568)	(0.064467)	(0.077027)	(0.111297)
HHI	0.224932 **	0.145757	0.083205	-0.004537	-0.044968	-0.012498	-0.088892	-0.103006	-0.013641	0.376960
	(0.102196)	(0.115458)	(0.133444)	(0.163556)	(0.205811)	(0.267998)	(0.336643)	(0.406102)	(0.559401)	(1.02946)
Foreign	0.000797	0.000317	0.000092	0.000028	0.000425	-0.000504	-0.001816	-0.001239	0.000554	0.003920
	(0.001519)	(0.001485)	(0.001719)	(0.002174)	(0.002429)	(0.002871)	(0.003651)	(0.005107)	(0.007643)	(0.011617)
Single	0.003208	0.000345	-0.003716	-0.027688	-0.028614	-0.031237	-0.065363	-0.097809	-0.125157	-0.185228
	(0.027324)	(0.024128)	(0.025496)	(0.029057)	(0.028587)	(0.033345)	(0.051656)	(0.076111)	(0.129414)	(0.244789)
MarketShare	-0.313075 ***	-0.355479 ***	-0.374844 ***	-0.426595 ***	-0.465487 ***	-0.547672 ***	-0.638735 ***	-0.777315 ***	-1.051126 ***	-1.687260 ***
	(0.042716)	(-0.043780)	(0.049463)	(0.056827)	(0.064779)	(0.083585)	(0.104331)	(0.132345)	(0.185793)	(0.335241)
SibMMC	-0.008923 *	-0.008646 *	-0.007795 *	-0.008193	-0.004943	-0.001264	-0.003328	0.001860	-0.000531	-0.000768
	(0.004781)	(0.004526)	(0.004613)	(0.005187)	(0.005989)	(0.006722)	(0.008924)	(0.010194)	(0.014064)	(0.024183)
CompMMC	0.001414	0.001032	0.000423	-0.001208	-0.002344	-0.002694	-0.00456	-0.008035 **	-0.013556 **	-0.023289 ***
	(0.001342)	(0.001335)	(0.001531)	(0.001827)	(0.001772)	(0.001993)	(0.002841)	(0.003798)	(0.005825)	(0.008862)
MarketMMC	-0.103037 *	-0.080277	-0.063143	-0.036771	0.027894	-0.014605	0.090462	0.203394	0.350699 *	0.613424
	(0.057002)	(0.052349)	(0.05442)	(-0.059290)	(0.063296)	(0.073199)	(0.112253)	(0.146882)	(0.208249)	(0.393434)

* p < 0.10; ** p < 0.05; *** p < 0.01

can be attributed to stochastic variation and because true defection is accompanied by large positive deviation. Therefore, we find evidence supporting H1. Figure 2.2 presents a graphical illustration of the results. As the graph shows, the effect of *CompMMC* varies across quantiles of sales growth deviation becoming more evident for larger growth deviations. This finding validates our suspicion of the constant association between positive sales growth and MMC across the sales growth distribution implied by the Tobit model in our case and further validates the usage of quantile regression.

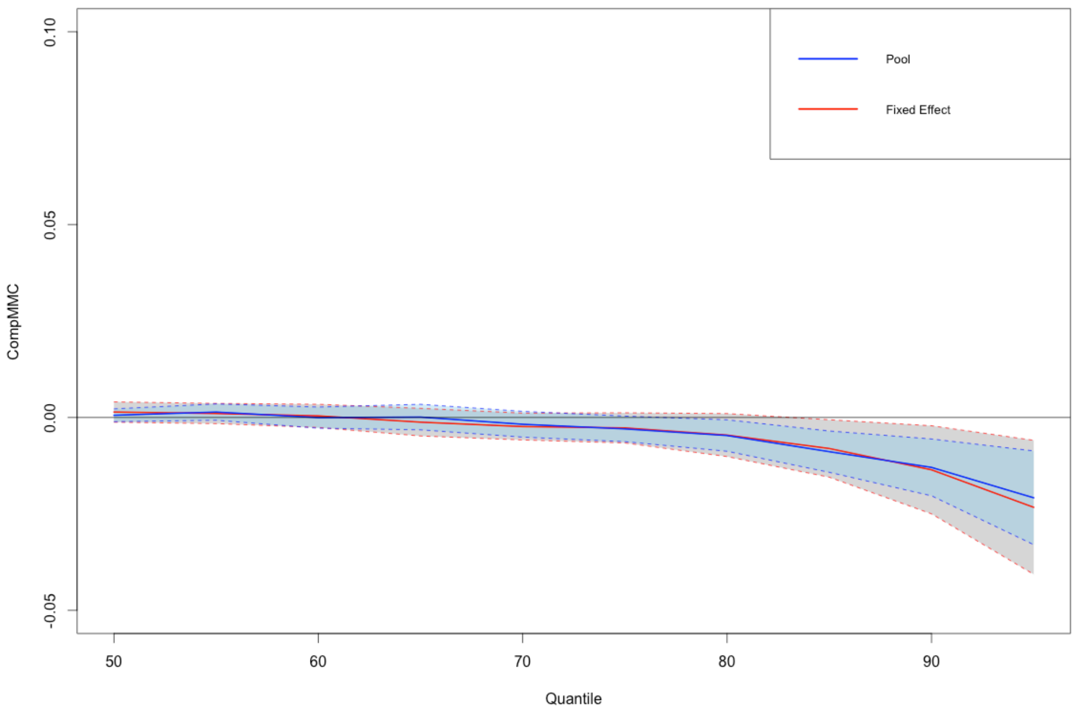

Figure 2.2 Effect of MMC with competing brands

Unlike the evident effect of MMC with competing brands, we find no statistically significant association between the positive sales growth deviation and MMC with siblings in either of the two models (see Figure 2.3). This result suggests that although an increase in the sheer number of MMC with siblings augments the detection probability, no significant evidence indicates that this increase will deter defection. Our result shows that brands do not appear responsive to MMC with siblings and that their defection behavior is not influenced by the increase in MMC with siblings. It therefore implies that, with all else equal and with the same amount of MMC with competing brands, brands having MMC with siblings are not more active in initiating mutual forbearance than brands without MMC with siblings. Thus, we also find evidence supporting H3.

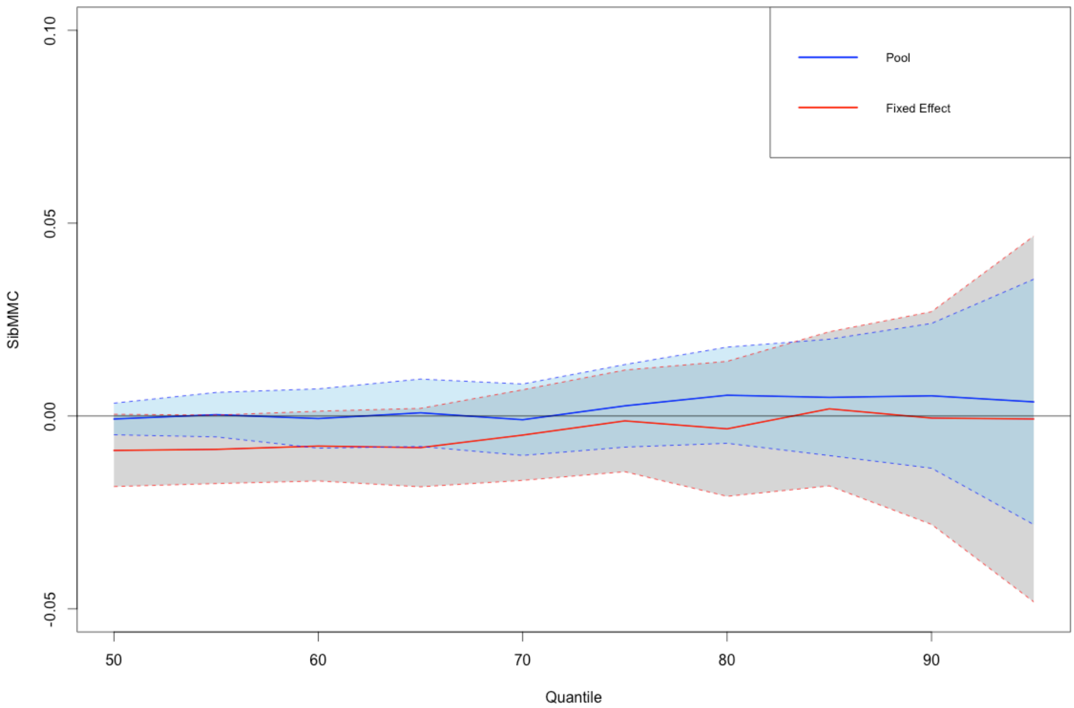

Figure 2.3 Effect of MMC with sibling brands

H2 is only partly supported because the two models diverge regarding the effects of market-level MMC. Despite having a significantly positive effect on sales growth deviation in the pooled model since the 85th quantile, the fixed effects model does not show significant effect of market-level MMC across the quantiles (see Figure 2.4). The results show that the effect size in the fixed model is smaller and the standard errors are larger.

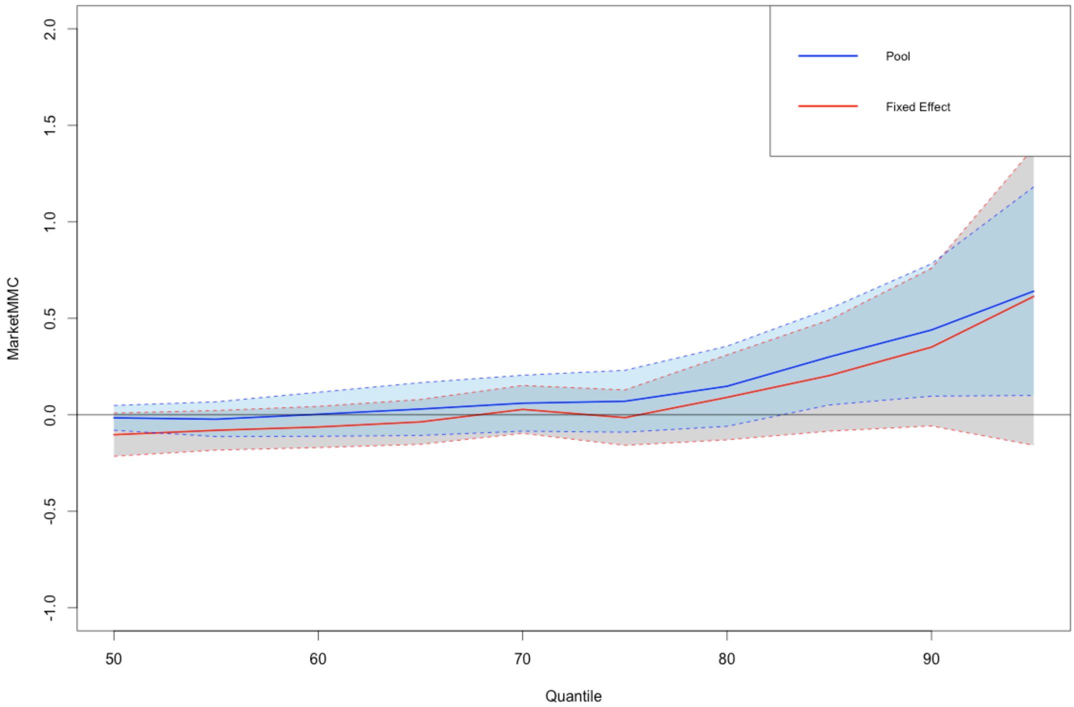

Figure 2.4 Effect of market-level MMC

We also consider the potential interaction effect between market-level MMC and brand-level MMC. Previous literature has reported only marginal significance of this effect and suggested the preference for a simpler model without interaction terms (Greve, 2008). Similarly, we do not find any significant interaction effect between market-level MMC and brand-level MMC in separate models. The significance of the main effects remains unchanged in those models. Because models with interaction between market-level MMC and brand-level MMC do not provide additional information. Thus, we do not report the estimation results of those models.

The finding on market sales growth confirms that high-growth markets will witness higher defection likelihood because all participants in such markets will fight for more market share. There is strong support for the argument that larger brands are less likely to defect, as the coefficient of the market share is statistically significant with large effect size across almost all the percentiles in both models. However, we do not find any evidence of the effect of market concentration on defection behavior. Therefore, higher market concentration does not necessarily make a market a more profitable place to defect, presumably because the higher market concentration did not bring about higher coordination among brands due to the deterioration of the overall industry financial environment. We do not find a significant effect of foreign brand counts. The single-market-brand indicator is significant only in the pooled model, presumably due to its limited within variation. However, this indicator is significant in only two of the ten quantiles in the pooled model. This implies that foreign brands and single market brands are not very different from domestic brands and multimarket brands in terms of their market behaviors.

2.5 Implication

Using a quantile regression analysis, MMC with sibling brands and competing brands is empirically studied to test the difference in their effects in terms of defection deterrence under imperfect observability. In summary, our main findings are as follows:

- Defection is unlikely if MMC with competing brands is sufficiently high. Therefore, MMC with competing brands functions effectively as a defection-deterrence mechanism.
- Increasing the amount of MMC with sibling brands does not seem to decrease the propensity of defection. Therefore, no evidence indicates that MMC with sibling brands functions effectively as a defection-deterrence mechanism.

Our work provides important managerial implications for group-level managers to validate the multi-brand multi-market overlapping strategy.

Our results indicate that, with the same number of MMC with competing brands, a brand that has MMC with its siblings does not have competitive disadvantage in the sense that it will not suffer from lower sales growth. In addition, with the same total amount of

MMC (with siblings and with competing brands combined), a brand that has MMC with its sibling brands will take more chances to strive for higher sales growth. It also implies that the stronger stance in competition taken by brands having MMC with their siblings may, but not necessarily, lead to sibling rivalry and cannibalization within groups. However, to maintain competitive edge, such competitive relationship can be essential for multi-brand multi-market manufacturing groups. Our finding validates automobile manufacturing groups' current business strategy of multi-brand, multi-market overlap, as these groups benefit from superior brand performance.

MMC and mutual forbearance can be a mixed blessing (Greve, 2008; Yu & Cannella, 2013). Although short-term profitability might be ensured, inertia will be bred and brands' competitiveness can be eroded in the long run. Thus, in the long run, markets can become more open, making mutual forbearance strategies more likely to fail (Ilinitch, D'Aveni, & Lewin, 1996). Therefore, automobile manufacturers must adjust their strategies to adapt to a changing competitive environment. Based on the results of this study, we offer some suggestions for multi-brand groups in designing an intra-group competition relationship.

I. Groups should align brands according to the group's strategic goals. Too-refined strategic goals may be difficult to align with an increase in the number of brands and the resulting intra-group competition. However, a simple goal, such as groups valuing market behavior in the interest of the overall group, should be conveyed to all brands.

II. Given that strategic goals are aligned, groups should tolerate or induce intra-group competition as a way to foster overall competitive efficiency, which can be achieved by designing incentives such as compensation packages to reward better performance. Performance-based resource allocation or introducing new brands can also induce competition. However, when competition is too high to easily align strategic goals, groups need to consider reducing the number of brands.

III. Given I) and II), groups should adopt multi-brand, multi-market overlap. As suggested by our results, this strategy is unlikely to put groups at a disadvantaged competitive position. Nevertheless, as business environments are rapidly changing, the optimal behavior for brands may be to inevitably form a coalition and to initiate mutual forbearance. In this case, if the resulting mutual forbearance is in significant opposition to the group's interest, groups need to reduce the overlap among sibling brands by either differentiating brands in terms of market focus or by reducing brands.

2.6 Conclusion and Limitation

Our paper is the first to study MMC with sibling brands and competing brands under imperfect observability in the automobile industry. Through the empirical analysis, we find that higher MMC with competing brands facilitates mutual forbearance. However, the same phenomenon does not necessarily apply to sibling brands. The resulting unwillingness of brands that have MMC with siblings to initiate mutual forbearance is not necessarily bad for the manufacturing group, as this will shield the group from having lower sales growth than single brand manufacturers. Our finding provides support for the business practices of multi-brand, multi-market automobile manufacturing groups. Applying quantile regression, we show the advantage of this method when the research interest lies in the non-central location of the dependent variable and when the conditional variance of the dependent variable is heterogeneous.

Although our paper offers important contributions to the existing literature, it also has some limitations. While product segments constitute valid markets used in MMC analysis, future research can extend this study by combining both product markets and geographic markets at the same time (Alcantara & Mitsuhashi, 2015). It offers the possibility to study mutual forbearance under imperfect observability on multiple dimensions. Incorporating both types of markets can lead to more insight into the study of MMC with sibling brands and competing brands across product segments and across geographic markets. In addition, replications should be conducted in different industries, as MMC can work differently in capital-intensive industries and labor-intensive industries, for example. This design can even provide a more robust analysis of the research question.

Moreover, in future research, a behavioral perspective should be considered. Specifically, in the context of MMC with sibling brands, the factor of managers at the brand level and at the group level can be included to relax the full rationality assumption. In addition, future studies can expand our study by including the group-level strategy variables, which offer the possibility to analyze the effectiveness of MMC under various higher-level strategy settings. The results can potentially provide crucial managerial implications for groups that govern multiple brands.

Furthermore, future studies can extend empirical models to test recent developments in theories regarding MMC under imperfect monitoring (Kobayashi & Ohta, 2008; Kobayashi & Ohta, 2012; Yamamoto, 2007). We wish our work would encourage more studies in related directions.

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3 The Social Exposure Effect of Coupon Trading on Coupon Redemption

Abstract

Digital coupons are gaining considerable momentum due to the combination of gloomy economic outlook and advanced digital technology. Compared to paper coupons, it is much more convenient for consumers to trade digital coupons. In this paper, we examine the phenomenon of coupon trading, which repeatedly expose consumers to product related information. Different from existing literature that focuses on coupon retailers as the source of exposure, we base our empirical analysis on social exposure induced among consumers themselves. We apply our analysis on a disaggregated user and product level longitudinal dataset from a Swiss online coupon service provider over a time span of 12 months. Our results suggest that due to repeated exposure towards product related information, coupon trading can effectively enhance coupon redemption likelihood. This study extends existing literature by bridging coupon literature with exposure effect, offering important implication to researchers and practitioners.

Keywords: digital coupon, coupon service provider, coupon trading, exposure effect, coupon redemption, multilevel modeling, event history analysis

3.1 Introduction

Nowadays, coupons are often digitalized, enabling them to be easily carried and exchanged among coupon users. Digital coupons are more convenient avenues for coupon usage compared to traditional paper coupons (Chiou-Wei & Inman, 2008). According to Inmar' s estimate, in 2013 along, the redemption of digital coupons in U.S. reached 66 million, marking a 141 percent increase over 2012 (Inmar, 2014). One important difference distinguishes digital coupons from traditional paper coupons is that consumers are enabled to collect and trade coupons freely.[5] The immediate result of the opportunity to trade coupons, apart from matching each other's needs, is the emergence of additional channels where consumers are exposed to product related information whenever other consumers suggest them for a trade. Such channels can take the form of a dedicated website (Hotcouponworld), a functional part of an online forum (Steam), a user group (Yahoo, Facebook) or even ad-hoc coupon trade clubs organized among peers, friends or colleagues.[6] It leaves us wondering whether coupon trading among consumers may increase coupon redemption rate due to the increased exposure towards coupons. This can be of vital importance for various online third-party coupon service providers, who emerged accompanying the boom in digital coupons and rely heavily on coupon redemption in their business models. Against this backdrop, we examine in this paper the social exposure effect of coupon trading on coupon redemption, which is the change in redemption likelihood attributed to coupon trading due to the exposure towards product related information induced among consumers themselves.

Our work is grounded in the general literature stream of exposure effects. The theoretical framework of exposure effects has a long history across different disciplines. It

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[5] By trading coupons, we refer specifically to the situation that a user gives coupons to another user and/or receives coupons in return. Thus, no real money transaction is involved in the process.

[6] Hotcouponworld: http://www.hotcouponworld.com/forums/coupon-trading/
Steam: https://steamcommunity.com/groups/Coupon-Trading-Group
Yahoo: https://groups.yahoo.com/neo/groups/Coupon_Exchange/info
Facebook: https://www.facebook.com/pages/Coupon-Exchange/165938863465201

has been applied to online settings in modern literatures (Chatterjee, Hoffman, & Novak, 2003) (Zhu & Zhang, 2010). Through empirical analyses built on a unique dataset with 1,923,405 coupon trade records, 32,603 users and 265 products from a Swiss online third-party coupon service provider over a time span of 12 months, we find that coupon trading positively affects consumers' coupon redemption likelihood due to the repeated exposure towards product related information.

This study makes contributions to both the academia and the industry. The importance of incorporating social elements as a marketing strategy in the coupon industry has been highlighted in previous literature (Dholakia, 2011) (Dholakia & Tsabar, 2011) (Dholakia, 2012) (Kumar & Rajan, 2012). With a special focus on the social exposure effect of coupon trading on coupon redemption, this work differentiate itself from previous work where coupon trading is monetary and its ability to expose consumers to product related information is consequently impossible to study (Su, Zheng, & Sun, 2014). It also differs from previous research where the source of the exposure is retailers and the trading-induced exposure among consumers themselves is overlooked (Venkatesan & Farris, 2012). Thus, our work extends the existing coupon literature. In addition, while the majority of existing coupon literature related to exposure effect has paid their attention on coupon manufacturers' sales of products, our study has a different research priority on the online coupon service providers' redemption incidents. The rising global interest in coupons as a result of economic recession and advance in information technology attracts much attention and effort from practitioners and entrepreneurs to establish their own coupon sites. Unlike coupon manufacturers/retailers, these coupon service providers heavily rely on coupon redemptions to generate revenues, to build up reputation, and to draw external investment. With dedicated research efforts on coupon redemption, our work provides important managerial implications for the operation of online coupon platforms.

Moreover, the contribution of this study is also empirical. Although coupon trading has existed for quite a while through the form of coupon exchange clubs or coupon corners within various online forums, related research is very scarce largely due to the problem of data availability. With our unique longitudinal dataset, we are able to empirically analyze the social exposure effect of coupon trading on coupon redemption on a disaggregated consumer- and product-level. Compared to the majority of coupon researches that are based on aggregated level of product/brand or consumers, a disaggregated analysis offers the opportunity to capture the complexity in consumers' behaviors across different products. Since consumers hold coupons on different products for different length of time before redemption or expiration, the empirical analyses are built on the multilevel framework due to its power on clustered data and its lack of requirement on balanced panel data. Specifically, we adopt a cross-classified discrete time event history analysis to account for the temporal dependency and the unobserved heterogeneity of both consumers and products. It is especially important for coupon studies since a consumer can have coupons on different product and coupons on the same product can be held by different consumers. Ignoring the temporal dependency and the non-nested data structure can lead to invalid standard errors, which impedes correct inference of the effect.

The fast-growing yet under-researched digital coupon practice calls for empirical studies to guide its future development as it is attracting more and more vendors and consumers due to high penetration of digital technologies. By applying the results of this research, marketers and managers can effectively utilize coupon trading to lift the redemption rate because it enables consumers themselves as source of advertisement on products.

The paper is organized as follows: in Section 2, we review related literatures and the theoretical framework. In Section 3, we present the general setting, our longitudinal dataset and the empirical model. The estimation results and robust checks are then presented and discussed in Section 4. Based on the results, we discuss both theoretical and practical implications, and conclude the paper in Section 5.

3.2 Related Literatures and Theoretic Framework

3.2.1 Digital Coupons and Online Third-Party Coupon Service Providers

Digital coupons are gaining more shares in total coupon usage thanks to the advancement of IT technology. Due to their unique characteristics such as easy dissemination, share and storage, digital coupons are more powerful than traditional coupons. Besides, they can more easily assume social functions than traditional coupons. This is best illustrated via the widely adopted practice of blending online digital coupons with social elements in recent years (Kumar & Rajan, 2012). Compared to traditional coupons, digital coupons also offer a far more direct and convenient vehicle than traditional coupons to reach consumers (Chiou-Wei & Inman, 2008). The paperless feature of digital coupons not only frees consumers from non-monetary efforts such as clipping the coupons or remembering to bring the coupons at redemption, it also makes social interactions among consumers such as exchanging their coupons more conveniently. Data collection on digital coupons is more readily available. It would be very difficult, if not impossible, to track trading activities on traditional coupons.

Accompanying the surge in digital coupons, a handful number of online third-party coupon service providers have emerged due to the lucrative business opportunities and revenue gains (Kumar & Rajan, 2012). The existence of online third-party coupon service providers, which usually take the form of a dedicated website or a conglomerate of websites, pool the resources of coupons and facilitate the redistribution of coupons among consumers. Traditionally, paper coupons and coupon manufacturers/retailers have been the center of the coupon literature. Recently, we have witnessed research efforts focused on coupon service providers, which has been overlooked in the past (Luo, Andrews, Song, & Aspara, 2014). Yet, we believe that there are unexplored areas within the domain of digital coupons and coupon service providers that demand thoughtful research. As a promotional strategy, one of the most important performance measurements of digital coupons, similar to traditional ones, is the redemption rate. This is especially true for online third-party coupon service providers as they generate revenue, build up reputation, negotiate terms with suppliers and draw external investment based on coupon redemptions. Therefore, it is very important for both the academia and the industry to find innovative ways to lift coupon service providers' redemptions rate. The pooled coupon and consumer resources on coupon service providers' platforms indicate the possibility of large-scale coupon trading activities. To explore viable business models for coupon service providers and to echo the call for more researches on coupon redemption behavior due to the increase in coupon usage (Venkatesan & Farris, 2012), we explore the social exposure effect of trading on coupon redemption in this paper.

3.2.2 Coupon Trading and Exposure Effect

In his seminal paper, Zajonc found that the mere repeated exposure is sufficient to enhance one's evaluation of the stimulus, which can be interpreted as preference (Zajonc, 1968) (Zajonc, 1980). Though not widely applied in coupon literature, mere exposure effect can surely fit in this stream of literature. According to the multibenefit theory, consumers do derive value from mere exposure to coupons (just seeing the promotion for a product) (Chandon, Wansink, & Laurent, 2000). This seems indicating that coupon trading can lead to value derivation and preference on the underlying product, operationalized here as the redemption of the corresponding coupons, because it repeatedly expose consumers to product related information.

As shown in Figure 3.1, the digital coupons studied in this paper contains both graphical and textual information on the product. With coupon trading enabled, a focal consumer will be exposed to this product related information when he receives trade requests

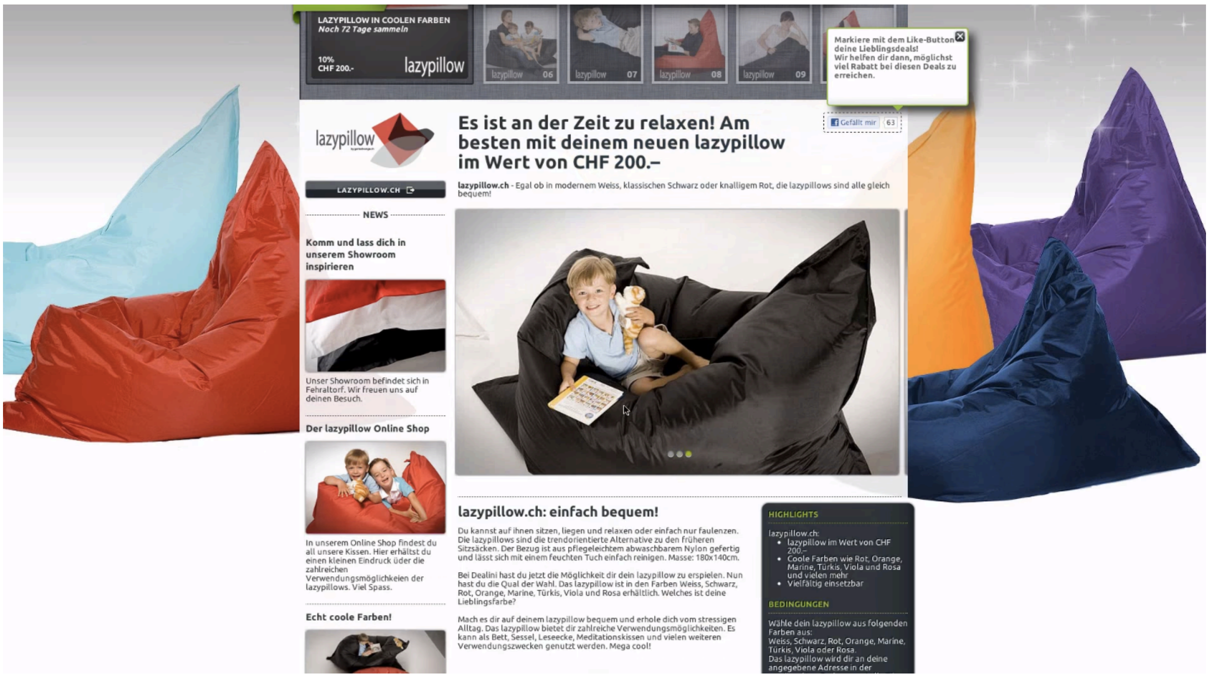

Figure 3.1 Example of a product on the platform

where trading partners offer coupons on the focal product to him. The more trade requests he has receives on the focal product, the more he has been exposed to such product related information. Therefore, based on the above-mentioned theories, we propose a positive relationship between the social exposure effect of coupon trading and coupon redemption:

- The cumulative number of trade proposals from which one has been offered coupons on a product is positively associated with his redemption likelihood of the product, given everything else equal.

Nonetheless, we also have to admit that with the increasing amount of digital coupons and trading activities, consumers' mental costs can also increase accordingly. When consumers are overwhelmed by the large amount of coupons and trading activities, the increasing burden on consumers to remember and to process relevant information would potentially compromise the social exposure effect of coupon trading. This also echoes the divergence regarding the pattern of exposure effect. While the perceptual fluency theory supports a monotonically increasing pattern of exposure effect (Bornstein & D'Agostino, 1992), an inverted U-shape saturation pattern is advocated by the two-factor theory (Berlyne, 1970). Therefore, to ensure the robustness of this study, we also consider an inverted U-shape pattern of the social exposure effect of coupon trading to reflect potential satiation in the effect. More details will be given in the modeling section.

Coupon trading has already existed in the forms of online forums' coupon corners or coupon exchange club, yet there is very limited research related to this phenomenon. To the best of our knowledge, Su et al.'s paper (2014) is the only work addressing the coupon-trading phenomenon. It should be noted that our study is very different from the work of theirs. We have a rather different research focus and research topic than theirs. By focusing on monetary-based coupon trading, Su et al. explore the benefit of price discrimination in coupon practice for coupon retailers and coupon manufacturers. In this study, however, we pay our research attention to non-monetary-based coupon trading. This distinction is vital for our research question because it is only possible to empirically quantify the social exposure effect of coupon trading on coupon redemption on non-monetary-based coupon trades. Moreover, we base our analysis on third-party coupon service providers rather than coupon retailers/manufacturers. Therefore, our work explores previously uncharted territory of coupon trading.

3.3 Data and Model

3.3.1 General Setting

This study collects data from a Swiss online coupon service provider that was founded at the end of 2011. The company, which prefers to remain anonymous, focused primarily on coupon distribution and coupon redemption for generating revenue. The most distinguishable feature of the company that differentiates it from competitors is the facilitated trading mechanism. Instead of making itself the sole source of disseminating product related information, the company facilitates online coupon trading where consumers are subject to additional exposure towards product related information. The company has witnessed a steady growth in its consumer base, which has grown at an annual rate of 114%.

Different categories of products are available on the platform, ranging across beauty products, electronic products, fashion products, food products, leisure/fun products, home products and travel products. Every product comes along with a set of ten unique digital coupons. Each coupon equates a ten percent discount off the product's listed price. The more unique coupons a consumer collects, the more discount he receives additively. Thus, the consumers can redeem the coupons and get the product by paying the remaining price after the discount conditioning on the number of unique coupons they have. Products are usually available on the platform for long enough time to ensure consumers with adequate time to collect and trade coupons.

Consumers are exposed to product related information in two ways. Firstly, every consumer receives two random coupons for daily login. These randomly issued coupons are very similar to traditional freestanding inserts (FSI) appearing on newspapers and direct mails in the sense that consumers passively receive them from coupon distributors. Secondly, coupon trading enables consumers to induce exposure towards product related information among them. To facilitate coupon trading, the company implemented a search engine on its platform. This enables consumers conveniently find others who possess coupons of a product that they are looking for. They can then send trade requests with their offers of coupons. Consumers who receive trade requests are then exposed to information on the products underlying the coupons.

3.3.2 Advantage of this study

The setting and data of this study provides two potential advantages. Firstly, as we mention earlier, the random coupons received upon daily login serve as a plausible proxy of

FSI. This provides us with an opportunity to compare the added value of coupon trading to the simple FSI without coupon trading. Secondly, every consumer is offered an online tutorial upon registration to learn the mechanism of the platform. Together with the facilitation of the in-platform search engine, the required effort on the consumer side to get involved in trading is minimum. Thirdly, the platform offers the opportunity to ship the redeemed products to consumers' delivery addresses. Previous literature has indicated that coupon usage can be negatively affected by the factor of being perceived 'cheap' (Dhar & Hoch, 1996) (Brumbaugh & Rosa, 2009). With the possibility of product shipping, interaction with other people such as shopping assistants at retailer sites can be avoided. These additional controlling factors make this study arguably more powerful than previous related researches.

3.3.3 Data

Our longitudinal dataset contains consumer and product information ranging from January 2012 to December 2012 for one full year. During this period, the platform records 1,923,405 coupon trades, 32,603 consumers, 265 products and a total number of 7,773 redemptions. As shown in Figure 3.2, the redemption rate has been rather low. Though reached around 1.3% at its peak, the redemption rate has constantly been below 0.5%[7]. During the period of this study, the company offered products in 8 different categories, namely automobile related products, beauty products, electronic products, fashion products, food products, leisure/fun products, home products and travel products.

The empirical analysis is built on a monthly level. Thus, our longitudinal data has the sample size of 2,224,838 observations. Our primary reasons of building the model on a monthly base are twofold. From the data and modeling point of view, a combination of the

[7] Though the redemption incidents had a generally increasing trend, the even faster increase in the consumer base has kept the redemption rate at a rather low level. The surge in redemption rate in March is likely due to more favored products on the platform.

large sample size and the complexity error structure in the cross-classified model indicate that a monthly analysis is more practical. A weekly or daily setup would result in the estimation of the model beyond our computational capacity in terms of both the memory and the computational time. Monthly setup can also eliminate any unwanted noise occurred at the daily and weekly level. More importantly, from the business point of view, a monthly analysis is in line with the operation of the platform and fits better for its business. The platform makes strategic moves based on their monthly financial reports. The executives are interested in monthly performance rather than weekly. Considering the fact that the platform does not vary its business strategy week by week, we deem that a monthly analysis is indeed adequate and appropriate for this study.

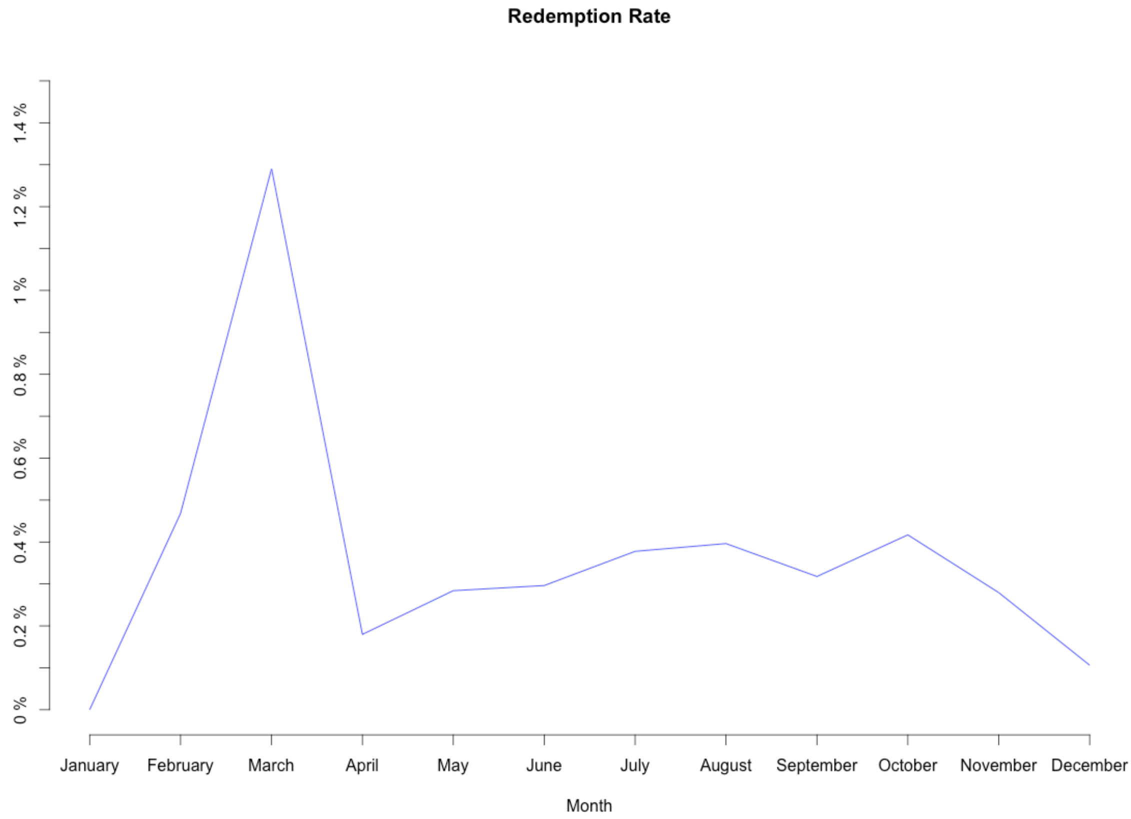

Figure 3.2 Overview of the redemption rate on the platform

3.3.4 Empirical Model

In this section, we present our empirical models. In essence, what we model is the binary outcome of whether a consumer redeems a product or not. However, ordinary logistic regression ignores temporal dependencies and leads to inefficient estimation and incorrect standard errors. Besides, ignoring consumer- and product-heterogeneity can also bias estimation results. Hence, we adopt multilevel discrete-time event history models as our modeling strategy. With the advancement in computing software, event history analysis with complex data structure has been widely used across different disciplines (Singer & Willett, 2003) (Steele, 2008). The discrete time hazard, defined as the conditional probability that coupons are redeemed in period i given that the redemption has not occurred in earlier periods, can be notated as: $h_i = Pr[y_i \neq 0 | y_s = 0, s < i]$

The corresponding event history model in this case can be estimated with the following form (we adopt the notation advocated by Browne, Goldstein & Rasbash (2001) for cross-classified models to avoid complex classification of variable subscripts):

$$\begin{aligned} logit(h_i) = \beta_0 &+ \beta_1 T_i + \beta_2 T\_Sq_i + \beta_3 Exposure_i + \beta_4 Likes_i + \beta_5 PastR_i + \beta_6 PastCR_i \\ &+ \beta_7 PastST_i + \beta_8 AvgH_i + \beta_9 OtherT_i + \beta_{10} Issue_i + \beta_{11} Tenure_i \\ &+ \beta_{12} Invite_i + \beta_{13} Refer_i + \beta_{14} Price_i + \beta_{15} RedDur_i + \beta_{16} Expire_i \\ &+ \beta_{17} Discount_i + \beta_{18} Ad_i + \beta_{19} Vol_i + \beta_{20} NumProduct_i + \beta_{21} Auto_i \\ &+ \beta_{22} Beauty_i + \beta_{23} Electro_i + \beta_{24} Fashion_i + \beta_{25} Food_i + \beta_{26} Fun_i \\ &+ \beta_{27} Home_i + \beta_{28} Q1_i + \beta_{29} Q2_i + \beta_{30} Q3_i + u^{(2)}_{product(i)} + u^{(3)}_{consumer(i)} \end{aligned}$$

$$u^{(3)}_{consumer(i)} \sim N(0, \sigma^2_{u(3)})$$

$$u^{(2)}_{product(i)} \sim N(0, \sigma^2_{u(2)})$$

Different from ordinary logistic regression, in this equation T and T_2 is a quadratic function of time that enters the model to parsimoniously capture the baseline hazard. The baseline hazard also indicates that duration dependence is assumed in the model. Event history analysis requires a meaningful starting time, after which the subjects are under risk of the occurrence of the event. In this study, we set the starting time as the first time a focal consumer acquires a coupon of the focal product, and the event being the redemption of the focal product by the focal consumer. T, in this case, is the months passed since the consumer acquired his first coupon on the focal product, given that he has not redeemed the product yet. Since every consumer can have coupons on multiple products at any given time and multiple consumers can hold coupons on the same product at any given time, our sample constitutes a cross-classified structure rather than a pure nested structure. The two-variance components $u_{consumer(i)}^{(3)}$ and $u_{product(i)}^{(2)}$ are used to capture the unobserved heterogeneity in consumers and products. The estimation results of these two parameters serve as a test on the assumption of unobserved heterogeneity (Singer & Willett, 2003).

As introduced in earlier section, the more trade requests a focal consumer has received on the focal product, the more he has been exposed to product related information. We use the cumulative trade requests (*UW_Expo*) that consumer k has received in which consumer k is exposed to product j to measure the social exposure effect of coupon trading in Model 1. To test if there is satiation in the social exposure effect of coupon trading, we also include quadratic terms of *UW_Expo* (i.e., *UW_Expo, UW_Expo_2)* in Model 2 to test the potential inverted U-shape pattern. The quadratic terms also serve as a test on the assumption of linear additivity (Singer & Willett, 2003).

3.3.5 Control Variables

To correctly reveal the social exposure effect of coupon trading, it is important to take consumers' personal attraction to different products into consideration. Coupon proneness is broadly defined as the increased propensity to respond to a purchase offer because the coupon form of the offer positively affects purchase evaluations (Lichtenstein, Netemeyer, &

Burton, 1990). Previous literatures suggest that coupon redemption is influence by general coupon proneness and product-category-specific coupon proneness (Bawa, Srinivasan, & Srivastava, 1997) (Swaminathan & Bawa, 2005). Inline with previous literatures, we include a set of variables (*Likes, PastR, PastCR*) to control consumer k's coupon proneness on product j. Consumers can 'like' a product by clicking the corresponding button on the platform. They can also remove their 'like' anytime they want. Hence, the product 'like' variable of consumer k on product j (*Likes*) is time varying in our study. Together with consumer k's general past redemption experience, (i.e., past redemption incidents (*PastR*) and his past redemption experience in the product category same as product j (*PastCR*), we control consumers' proneness across different products.

Homophily is another influential factor in our analysis. Previous research has suggested that consumers are more likely to interact with people who are similar to them (Feick & Higie, 1992). In our case, active consumers may tend to engage in trading activities with other consumers with relatively similar active level. We investigate the extent to which such similarity among trading partners affects consumers' redemption probability. To capture the homophily between a focal consumer and his trading partners, we adopt a method similar to the work by Nitzan & Libai (Nitzan & Libai, 2011). We use three variables to capture the similarity in activity level: the cumulative number of products of which at least one coupon of the product was possessed (*CProduct*), the cumulative number of trades initiated (*CTrads*), and the cumulative months that a focal consumer log onto the platform for at least once (*CMonth*). Equal weights are assigned for each variable, and the sum of the weighted measures is used to evaluate the homophily between the trading partners. We now explain in detail how the similarity measure is composed. Instead of deciding a match/no match of each variable between the trading partners on a rather subjective criterion, we adopt a ratio measure to indicate consumer k's similarity to his trading partner m:

$$H_{k,m} = \frac{1}{3}\times[(1 - \frac{|CDeal_k - CDeal_m|}{max(CDeal_k, CDeal_m)}) + (1 - \frac{|CTrade_k - CTrade_m|}{max(CTrade_k, CTrade_m)}) + (1 - \frac{|CMonth_k - CMonth_m|}{max(CMonth_k - CMonth_m)})]$$

This measure is bounded on [0,1] with 1 indicating full match and 0 for no match. Based on this measure, we can calculate consumer k's average homophily with his trading partners (*AvgH*) in month t as follows:

$$AvgH_{k,t} = \frac{\sum_{m \in TP_{k,t}} H_{k,m}}{N_{TP_{k,t}}}$$

where m is a trading partner of consumer k ($m \in TP_{k,t}$) in month t and $N_{TP_{k,}}$ is the total number of consumer k's trading partners in month t.

Selection is a concern over the validity of this study. Consumers that self-select themselves into frequent exchange of coupons with others can be systematically different from those who exchange coupons less frequently in terms of both the propensity to redeem coupons and the likelihood to receive trade requests. In another word, more involved consumers may be more likely to receive more trade requests, having more exposure towards coupons and they are also more likely to redeem them. To avoid potential selection bias and endogeneity, we need to control how involved consumers are. Arguably, more involved consumers will be more active in making referrals and be more successful in both trading and redemption. Hereby, we include consumers' referral intensity (*Refer*), which is measured by the cumulative number of people whom they have successful invited on to the platform; their past successful trading experience (*PastST*) in the model; and consumers' past redemption experience (*PastR*) to make sure the social exposure effect of coupon trading captured in the model is not attributed to the alternative explanation of consumer involvement.

Several other consumer side variables are included in our model. As we argued in earlier sections, the increase in coupon trading may also induce mental burden on consumers with respect to memorizing and processing information. Hence, by including monthly trading activities by consumers on products other than the focal one (*OtherT*) in the model, we investigate the potential downside of coupon trading. One of the advantages of this study, as explained earlier, is that in our case the randomly issued coupons upon daily login functions as a proxy to FSI. This offers a plausible comparison between the effect of the exposure towards FSI and the social exposure effect of coupon trading. We therefore include consumers' cumulative receipt of coupons on the focal product, which are issued upon daily login (*Issue*). Other variables on the consumer side include the tenures of consumers on the platform (*Tenure*), measured by the number of months since consumers first login on the platform; whether consumers were invited to the platform or not (*Invite*).

On the product side, we include time invariant product characteristics such as product prices (*Price*), products' redemption durations (*RedDur*) and product category dummies (*Auto, Beauty, Electro, Fashion, Food, Fun, Home*). Time varying product variables include the remaining time until redemption expiration of the focal product (*Expire*) and the percentage discounts (*Discount*) enjoyed by consumers. It is worth noting that since the cumulative savings on products which consumers can enjoy depend on consumers' possession of different coupons on the products, product discounts (*Discount*) in our study is thus time varying and consumer specific. Monthly advertising expenditure on the focal product (*Ad*) and its monthly total on-platform trading volume (*Vol*) are also included.

We additionally control factors such as product availability and seasonality through the monthly number of products available on the platform (*NumProduct*) and the quarter dummies (*Q1, Q2, Q3*). All variables are mean-centered whenever appropriate. In Table 3.1, we report the definition and the summary statistics of the variables. Before proceeding to the estimation issues, we spend a few lines giving an overview of the summary statistics. Average consumers' redemption experience is low, which is not surprising given the overall low redemption rate on the platform. On average, consumers are not very similar to their trading partners. The monthly trading activities on non-focal products are moderate for average consumers. However, their effect on mental cost, which might affect redemption likelihood, is unknown. Product availability seems abundant on the platform and the time for redemption is enough for consumers. It is relatively difficult for consumers to collect coupons on a focal product simply through daily login. This can explain the fact that trading volume is high, which shows a strong consumer base and user engagement on the platform. This again underscores the importance to study the social exposure effect of coupon trading. The platform does not spend heavily on advertising neither does it rely on referral for consumer acquisition since average consumers' referral intensity is pretty low. The consumer base of the platform and the relatively low discount at which consumers redeem products show the potential of digital coupon and coupon trading as a lucrative business practice.

Table 3.1 Definition of variables and summary statistics

Variable	Definition	Mean	Std. Dev.
UW_Expo	Unweighted exposure effect	1.745625	5.258755
PastR	Consumers' past redemption experience	0.7169556	2.097253
PastCR	Consumers' past category-specific redemption experience	0.1315512	0.5970338
PastST	Consumers' past successful trading experience	39.31887	94.04235
AvgH	Consumers' average homophily	0.3616225	0.2079652
OtherT	Consumers' monthly trading activities on non-focal products	23.72214	91.57626
Issue	Consumers' cumulated received coupons upon daily login	0.4314939	0.756912
Tenure	Consumer tenure	3.651432	2.448263
Refer	Consumers' previous referral intensity	0.2381616	1.95027
Price	Prices of products	428.9115	807.7141
RedDur	Redemption durations of products	1.648273	1.285504
Expire	Time to redemption expiration of products	1.572884	1.610407
Discount	Discounts of products	0.1122133	0.1317452
Ad	Products' monthly advertising expenditure	33.6392	157.2012
Vol	Products' monthly trading proposal volumes	2150.312	2685.471
NumProduct	Monthly available products on the platform	63.38418	9.498872

Detailed operationalization of variables is presented in the 'Empirical Model' section

Quasi-likelihood methods (MQL, PQL), unlike MCMC (Monte Carlo Markov Chain), have been shown to bias the results when estimating models with non-normal response variables (Rodriguez & Goldman, 1995) (Goldstein & Rasbash, 1996). In addition, cross-classified data structure induces much less memory burden when estimated via MCMC rather than IGLS (Iterative Generalized Least Squares) (Rasbash & Browne, 2008). Therefore, the binary outcome with cross-classified data structure leads us to adopt a Bayesian approach. The model is estimated using MCMC implemented in the software MLwiN Version 2.34 (Rasbash, Steele, Browne, & Goldstein, 2014) (Browne W. J., 2014) (Leckie & Charlton, 2013). Diffuse priors are used to ensure coefficients are not affected by starting values and prior specifications (Venkatesan & Farris, 2012). We use the default priors provided by MLwiN, namely gamma priors are used for the variance parameters ($\sigma^2_{u(3)} \sim Gamma(0.001,0.001), \sigma^2_{u(2)} \sim Gamma(0.001,0.001)$). And for the rest of parameters, uniform priors are used ($p(\beta) \propto 1$). All the models are estimated with a burn-in length of 5,000 iterations and 80,000 runs to achieve effective sample size (ESS) over 100 for all variables and variance components. To improve mixing, the reparameterization methods of orthogonalization and hierarchical centering is used (Browne, Steele, Golalizade, & Green, 2009). Orthogonalization replaces the set of covariates with an alternative group of covariates that span the same parameter space but are orthogonal. Hierarchical centering reparameterizes the model by replacing the residuals and centering them around a function of the covariates. In our work, the models are centered at the consumer level. Given the size of the data and the complexity of the models, estimation is cumbersome and time consuming. The whole estimation is run on multiple instances on Intel® Xeon® processors with 2.27GHz, 2.39GHz CPUs and 20.0GB internal memory.

3.4 Results

3.4.1 General Model Fit

In terms of model fit, we compare models using the Deviance Information Criterion (DIC) (Spiegelhalter, Best, Carlin, & van der Linde, 2002). The estimation results of Model 1-2 are present in Table 3.2. Model 1 (DIC: 31273.9543), which operationalize the social exposure effect of coupon trading as cumulative trade requests received, serves as the baseline model of our analysis. In Model 2 (DIC: 31241.0058), a quadratic function of the social exposure effect of coupon trading (i.e., *UW_Expo* and *UW_Expo_2*) is used to investigate potential satiation in the effect. The DIC indicates that the inclusion of quadratic terms improves model fit. The variance components (i.e., the consumer and product random effects) in both models show significant results. This confirms the validity of our cross-classified modeling strategy.

3.4.2 Exposure Effect

The positive and significant result of *UW_Expo* (0.008362 (0.001296)) in Model 1 supports our hypothesis that coupon trading increases coupon redemption likelihood due to the repeated exposure towards product related information induced among consumers themselves. On the other hand, we also find evidence that an overwhelming amount of such social exposure can lead to a satiation in its positive effect. The result of Model 2 suggests that if certain threshold is passed, the positive social exposure effect of coupon trading gradually diminishes (*UW_Expo:* 0.017825 (0.002236); *UW_Expo_2:* -0.000085 (0.000018)).[8] Our result is thus empirically in line with the two-factor theory which suggests that the positive effect of repeated exposure can diminish due to satiation. The positive effect of coupon trading due to social exposure can also be translated into higher revenue gains for the platform. Conditional on the holding time of coupons and on the current discount, the

[8] It is worth noting however that around 99% of our sample does not cross the inflection point and hence not suffering from the diminishing effect.

social exposure effect of coupon trading leads to a higher redemption likelihood, meaning that consumers will be more likely to spend money on products and the duration of time until consumers spending money on products is shorter, ceteris paribus. This is critical for online coupon service providers, a point that we will discuss later in the paper.

Table 3.2 Results of the main analysis

	Model 1			Model 2		
Intercept	-11.535307	(0.290924)	***	-11.532254	(0.289521)	***
T	0.135775	(0.037037)	***	0.121488	(0.036733)	***
T_2	-0.214405	(0.008747)	***	-0.212644	(0.008667)	***
UW_Expo	0.008362	(0.001296)	***	0.017825	(0.002236)	***
UW_Expo_2				-0.000085	(0.000018)	***
Likes	0.387943	(0.042042)	***	0.337724	(0.042713)	***
PastR	0.009084	(0.01058)		0.009251	(0.010592)	
PastCR	0.040464	(0.020458)	**	0.038472	(0.020746)	*
PastST	0.000384	(0.000234)		0.000345	(0.00023)	
AvgH	1.748645	(0.159069)	***	1.720616	(0.159818)	***
OtherT	0.000467	(0.000137)	***	0.000434	(0.000135)	***
Issue	0.065061	(0.012191)	***	0.065329	(0.01217)	***
Tenure	-0.012207	(0.012795)		-0.008677	(0.012702)	
Invite	-0.117162	(0.050896)	**	-0.113668	(0.051917)	**
Refer	0.005538	(0.005573)		0.005362	(0.005489)	
Price	-0.000057	(0.000062)		-0.000054	(0.000062)	
RedDur	0.304391	(0.084334)	***	0.308228	(0.084032)	***
Expire	-0.786584	(0.0398)	***	-0.786533	(0.039537)	***
Discount	14.440729	(0.152794)	***	14.31478	(0.13979)	***
Ad	0.000781	(0.000163)	***	0.000778	(0.000164)	***
Vol	0.00001	(0.00001)		0.000008	(0.00001)	
NumProduct	0.01638	(0.002659)	***	0.016172	(0.002625)	***
Auto	1.096499	(0.659777)		1.075955	(0.693865)	
Beauty	0.25862	(0.436908)		0.257903	(0.453691)	
Electro	2.68306	(0.387942)	***	2.671043	(0.374534)	***
Fashion	0.913535	(0.313401)	***	0.934004	(0.310913)	***
Food	0.884439	(0.32909)	***	0.910648	(0.346251)	***
Fun	0.444715	(0.329314)		0.431771	(0.348762)	
Home	0.247497	(0.309489)		0.281731	(0.320831)	
Q1	1.099406	(0.187309)	***	1.099814	(0.188186)	***
Q2	-0.272142	(0.124487)	**	-0.267875	(0.123771)	**
Q3	-0.271304	(0.075343)	***	-0.269098	(0.075965)	***
Consumer Random Effect	1.230165	(0.07622)	***	1.22823	(0.070151)	***
Product Random Effect	1.6026	(0.173297)	***	1.596447	(0.171799)	***
DIC:	31273.9543			31241.0058		

3.4.3 Other Variables

The control variables also show interesting results. As the results are largely comparable, we base the discussion on the baseline models. The curvilinear baseline hazard suggests that an average consumers' likelihood to redeem a product first increases then decreases along the holding duration of coupons on that product (*T:* 0.135775 (0.037037); *T_2:* -0.214405 (0.008747)). This finding is expected as consumers' interest and motivation rises at first but can fade away later as impatience grows. We use product-likes, past general redemption experience and past category-specific redemption experience to capture consumers' coupon proneness. The results of these variables largely confirm the effect of coupon proneness on redemption likelihood. Though the effect of general redemption experience is insignificant, product-likes and category-specific redemption experience show positive and significant results (*Likes:* 0.387943 (0.042042); *PastCR:* 0.040464 (0.020458). We also use consumers' past redemption experience together with referral intensity, past successful trading experience to control self-selection. However, the results suggest that more involved consumers may not necessarily be more likely to redeem products. We find that homophily positively influence coupon redemption likelihood. Consumers may tend to engage in trading activities with others who have relatively similar active level. The result suggests that such similarity among trading partners positively affects their redemption probability (*AvgH:* 1.748645 (0.159069)). Additional trading activities on coupons of other products do not seem to pose heavy mental burden on consumers. On the contrary, there seems to be a positive spillover effect as trading activities on coupons of other products actually increase the redemption likelihood of the focal product (*OtherT:* 0.000467 (0.000137)), presumably due to the fact that the digitalized clipping and trading system of coupons eases consumers' routine tasks on managing their coupon. Those who have stayed on the platform for longer time do not necessarily have a higher (or lower) propensity to redeem, as *Tenure* is insignificant. Consumers who were invited to the platform are less motivated as their redemption likelihood is lower (*Invite:* -0.117162 (0.050896)). As we introduced in earlier sections, the randomly issued coupons upon daily login serve as a proxy of FSI. Compared to the social exposure effect of coupon trading, the results indicate that 1) the social exposure effect of coupon trading induced by consumers themselves indeed further increases product redemption likelihood aside from the exposure to FSI; 2) however, the social exposure effect of coupon trading is not as strong in magnitude as the effect of the exposure to FSI (*Issue:* 0.065601 (0.012191)). Similar to findings of previous literature, our results also suggest that product discount, rather than product price, is a more critical factor that influences consumer coupon redemption behavior (Luo, Andrews, Song, & Aspara, 2014). Product price is insignificant while the discount shows positive and significant result (*Discount:* 14.440729 (0.152794)). Intuitively, this finding is in line with the common sense that consumers are motivated to use coupons due to the discount they receive rather than the price of the product itself. A higher price signals that an average consumer may have to spend more on the product while a higher discount signals more monetary savings. Time to expiration negatively affects redemption rate, indicating that consumers are patient enough to wait until the last moment to make their decision whether to redeem coupons hoping for collecting larger discount before the expiration (*Expire:* -0.786584 (0.0398)). Products that have longer redemption duration have a higher chance to be redeemed (*RedDur:* 0.304391 (0.084334)). Advertising lifts product redemption probability (*Ad:* 0.000781 (0.000163)). Product abundance is positively associated with consumers' coupon redemption likelihood (*NumProduct:* 0.01638 (0.002659)). From the results, electronic products (2.68306 (0.387942)), fashion products (0.913535 (0.313401) and food products (0.884439 (0.32909)) appear to be more popular than the rest of product categories. Among these product categories, electronic products are evidently the most attractive. The quarter dummies (*Q1*, *Q2 and Q3*) indicate seasonal fluctuation in consumers' product redemption likelihood.

3.4.4 Additional Assumption Test & Robust Checks

We further ensure the robustness of the analysis by testing the proportionality assumption and by using different operationalization of the social exposure effect of coupon trading. Specifically, we test the assumption of proportionality in accordance of Singer & Willett (2003) by introducing interaction terms between the substantive variable (i.e., *UW_Expo*) and the baseline hazard function (*T, T_2*) in Model 3. The result is presented in Table 3.3

The main effect of the social exposure effect of coupon trading remains positive and significant (*UW_Expo:* 0.010906 (0.001481)). Its interaction with the baseline hazard suggests that the baseline hazard varies with different levels of exposure. Hence, the hazard is non-proportional. The interaction also indicate that the social exposure effect of coupon trading is magnified at first, but later fading away with time (*T×UW_Expo:* 0.006132 (0.001031), *T_2×UW_Expo:* -0.001568 (0.000445)). We would like to note that the time varying effect does not compromise in any way our earlier conclusion on the social exposure effect of coupon trading. Variables' primary effects are properly assessed only when no interaction terms involving them are included in the model (Aiken & West, 1991).

In the second robust check, we operationalize the social exposure effect of coupon trading in two additional ways different from the one used in the main analysis. In the first operationalization, we measure the social exposure effect of coupon trading as the round-weighted cumulative number of trade requests received (*W_Expo*). Since the trading process is composed of offers and counter offers, one trade can include multiple rounds. Consumers with low involvement in trading activities may lack motivation to process the product related information to which they are exposed, thus rendering the social exposure effect of coupon trading less effective (Leclerc & Little, 1997). The more rounds (alternative offerings between the trading partners) in a trade, the more involved the consumers are in that trade.

Table 3.3 Results of the non proportionality test

	Model 3		
Intercept	-11.601924	(0.27825)	***
T	0.053369	(0.038981)	
T_2	-0.194574	(0.010796)	***
UW_Expo	0.010906	(0.001481)	***
TxUW_Expo	0.006132	(0.001031)	***
T_2xUW_Expo	-0.001568	(0.000445)	***
Likes	0.388259	(0.042518)	***
PastR	0.009767	(0.010617)	
PastCR	0.038654	(0.020538)	*
PastST	0.000293	(0.000233)	
AvgH	1.73134	(0.160669)	***
OtherT	0.0006	(0.000136)	***
Issue	0.066182	(0.012187)	***
Tenure	-0.009754	(0.012779)	
Invite	-0.118202	(0.052364)	**
Refer	0.005898	(0.005527)	
Price	-0.000053	(0.000061)	
RedDur	0.298716	(0.082601)	***
Expire	-0.804758	(0.040048)	***
Discount	14.497441	(0.155984)	***
Ad	0.000787	(0.000165)	***
Vol	0.000014	(0.00001)	
NumProduct	0.017268	(0.002656)	***
Auto	0.996526	(0.664596)	
Beauty	0.170172	(0.46113)	
Electro	2.642186	(0.378784)	***
Fashion	0.894591	(0.303016)	***
Food	0.87135	(0.323049)	***
Fun	0.415757	(0.340089)	
Home	0.231869	(0.312802)	
Q1	1.09691	(0.186771)	***
Q2	-0.233096	(0.124318)	*
Q3	-0.273738	(0.075648)	***
Consumer Random Effect	1.247409	(0.077177)	***
Product Random Effect	1.605405	(0.174129)	***
DIC:	31229.2673		

*, ** and *** indicate the significance levels are at 10%, 5% and 1%

With this operationalization (Model 4), we intend to exam whether the positive relationship between coupon trading and coupon redemption (due to the exposure towards product related information induced by consumers themselves) are affected by consumers' involvement level in trades.

In the second operationalization, we separate the social exposure effect of coupon trading into two parts. Previous studies on the exposure effect in coupon practice have unanimously modeled the exposure effect within the context that consumers actually receive the coupons. However, mere exposure effect can take place when the stimuli are just accessible to individuals' perception (Zajonc, 1968). In coupon trading, some coupons actually exchanged while others are offered during trades but eventually not exchanged due to the failure to reach mutual agreement or the change of offers during the trades. Hence, grounded in the mere exposure effect theory, we use the cumulative number of coupons on a focal product that are actually received by the focal user in trading (*R_Expo*) as the first part of the social exposure effect of coupon trading, which is in line with previous coupon literature on exposure effect. Moreover, we use the cumulative number of coupons on a focal product that have been offered to but eventually not received by the focal consumer (*NR_Expo*) as the second part of the social exposure effect of coupon trading. Therefore, in Model 5, we intend to test whether coupon trading positively affects coupon redemption even without the actual receipt of coupons. The results of Model 4-5 are presented in Table 3.4.

The two alternative operationalizations of the social exposure effect of coupon trading both show positive and significant results (*W_Expo:* 0.004018 (0.000666); *R_Expo:* 0.016528 (0.003386), *NR_Expo:* 0.007342 (0.001098)). The result suggests that our finding of the positive effect of coupon trading on coupon redemption due to the consumer-induced exposure towards product related information is consistent across different operationalizations. In addition, it also suggests that such effect can sustain even without the actual receipt of coupons, indicating that mere visual stimulus also works.

Table 3.4 Results of the different operationalization of the exposure effect

	Model 4			Model 5		
Intercept	-11.515741	(0.278665)	***	-11.594684	(0.279397)	***
T	0.137907	(0.036757)	***	0.131107	(0.036716)	***
T_2	-0.214414	(0.008757)	***	-0.213205	(0.008754)	***
W_Expo	0.004018	(0.000666)	***			
R_Expo				0.016528	(0.003386)	***
NR_Expo				0.007342	(0.001098)	***
Likes	0.398882	(0.041445)	***	0.389339	(0.041537)	***
PastR	0.009473	(0.010567)		0.010187	(0.010502)	
PastCR	0.04085	(0.020518)	**	0.037496	(0.020442)	*
PastST	0.00035	(0.000231)		0.000304	(0.000233)	
AvgH	1.746848	(0.161649)	***	1.747424	(0.163088)	***
OtherT	0.000448	(0.000136)	***	0.000406	(0.000137)	***
Issue	0.065005	(0.012081)	***	0.068031	(0.012403)	***
Tenure	-0.011853	(0.012746)		-0.010016	(0.012824)	
Invite	-0.118668	(0.051236)	**	-0.112449	(0.051646)	**
Refer	0.005455	(0.005507)		0.005578	(0.005598)	
Price	-0.000055	(0.000062)		-0.000046	(0.000062)	
RedDur	0.293333	(0.082718)	***	0.282772	(0.08326)	***
Expire	-0.781765	(0.039886)	***	-0.784736	(0.039089)	***
Discount	14.42207	(0.14678)	***	14.330212	(0.146452)	***
Ad	0.000793	(0.000165)	***	0.000804	(0.000165)	***
Vol	0.000009	(0.00001)		0.000008	(0.00001)	
NumProduct	0.016351	(0.002662)	***	0.016532	(0.002692)	***
Auto	1.101743	(0.6838)		1.140393	(0.672537)	*
Beauty	0.228539	(0.457325)		0.262205	(0.468824)	
Electro	2.669072	(0.372786)	***	2.688276	(0.373438)	***
Fashion	0.929861	(0.295993)	***	0.937092	(0.3123)	***
Food	0.879592	(0.332619)	***	0.888411	(0.326876)	***
Fun	0.43856	(0.331004)		0.454282	(0.342571)	
Home	0.244444	(0.310845)		0.261114	(0.312166)	
Q1	1.088831	(0.190316)	***	1.098064	(0.189133)	***
Q2	-0.275761	(0.126045)	**	-0.262599	(0.125836)	**
Q3	-0.275409	(0.076337)	***	-0.271641	(0.076575)	***
Consumer Random Effect	1.217048	(0.072276)	***	1.245912	(0.0722)	***
Product Random Effect	1.592132	(0.172842)	***	1.61454	(0.173683)	***
DIC:	31284.339			31223.5423		

*, ** and *** indicate the significance levels are at 10%, 5% and 1%

3.5 Implication & Conclusion

At first glance, coupon trading seems a rather new phenomenon born under the background of the digital era. In fact, however, it has existed for quite a while in a rather undistinguished way. Coupon exchange clubs and coupon corners in online forums are traditionally the places where coupon trading takes place. Nonetheless, such scattered occurrences in real life practice provide us with very limited opportunities to research on topics related to coupon trading. Coupon trading can be an important way to improve coupon redemption probability. Not only does it facilitate consumer collecting and accumulating monetary savings, but also repeatedly expose consumers towards product related information, which can subsequently increase the likelihood of coupon redemption. More importantly, such effect is induced among consumers themselves rather than forced by coupon service providers. With a unique dataset of 32,603 consumers and 265 products from an online third-party coupon service provider, this study is the first empirical work aiming to quantify the social exposure effect of coupon trading. Through a cross-classified discrete time event history analysis, our results confirm that coupon trading can increase coupon redemption likelihood due to the consumer-induced exposure towards product related information. Together with other variables included in our empirical models, this study provides important implications to the academia and the industry.

3.5.1 Implication for Theory

In this paper, we extend existing coupon literature by empirically investigating the social exposure effect of coupon trading on coupon redemption within the context of digital coupons and coupon service providers. With the development of digital technology, digital coupons are prospering and trading coupons are thus becoming more convenient and common. However, there is very little research on the effect of coupon trading. Therefore, our finding of the positive effect of coupon trading on coupon redemption due to consumer-induced exposure towards product related information implies new research areas and topics in coupon studies.

Previous studies have shown that by including advertisement in coupons or customizing coupons by coupon manufacturers or retailers can positively influence consumers' purchasing behavior (Bawa & Shoemaker, 1989) (Srinivasan, Leone, & Mulhern, 1995) (Leclerc & Little, 1997) (Venkatesan & Farris, 2012). In this paper, we show that coupon trading can also be a channel to induce exposure towards product related information, and that consumer themselves function as the source of the exposure. This study suggests that apart from initiations directed by coupon manufacturers and retailers, other forms and sources of the exposure towards product related information shall be considered and explored in future coupon studies.

Our result also suggests that the social exposure effect of coupon trading does not grow linearly and exhibits a diminishing pattern with respect to both the amount of exposure and the duration of time. This finding further bridges the mere exposure effect literature and the coupon literature in the sense that future coupon research related to exposure effect shall not limit itself to the linear operationalization and shall consider potential time varying effect.

We also extend the coupon literature by studying market participant beyond the usual scope of coupon manufacturers or retailers. Focusing on a new but important player in modern coupon practice, namely online third-party coupon service providers, which emerge in the market due to the increasing popularity of digital coupons and rely heavily on coupon redemption rate in their business models, our work shows rich research opportunities on these coupon platforms and echoes previous researches' call for more studies on coupon redemption rate (Musalem, Bradlow, & Raju, 2008).

Besides our main findings on the social exposure effect of coupon trading, we also confirm findings in pervious literature that monetary savings instead of price motivates consumer to redeem products (Luo, Andrews, Song, & Aspara, 2014). Moreover, compared to the majority of existing coupon literature, we not only build our model on a disaggregated consumer-product level, but also consider unobserved heterogeneity in both consumers and products. Ignoring the unobserved heterogeneity on either of the two levels can lead to biased standard errors. Within the multilevel modeling framework, we extend prior studies on coupons by taking the cross-classified data structure of our sample into consideration. The significant consumer and product heterogeneity shows the feasibility and necessity to consider both product and consumer heterogeneity in coupon studies.

3.5.2 Implication for Practice

Our work also provides business implications for coupon service providers. The fact that digital coupons, which become more and more widely adopted as a marketing tool, suffer from low redemption rate makes our work highly relevant. Our result suggests that coupon service providers need to keep offering attractive products and discounts on the platform to increase redemption rate. Besides these measures, we also suggest that coupon platforms facilitate interactions among consumers and make consumers aware of the possibility to trade coupons. This is especially important as our results on the baseline hazard show that the redemption likelihood drops if coupons are held for too long. With coupon trading, consumers may collect discount faster and thus shorten the holding period. More importantly, coupon trading can increase the redemption likelihood and compensate the drop in redemption likelihood in the long term due to consumer-induced exposure towards product related information. Such social exposure effect is robust and consistent since different operationalization all report positive and significant results. This finding provides very useful implications to coupon service providers in the sense that coupon trading makes consumers more likely to pay for redemption and shortens the time it takes before consumers pay for redemption. Coupon service providers can thus collect revenue and cover their cost more effectively and more quickly, which are crucial factors to sustain in the market. When coupon trading is facilitated, every consumer can function as a potential source of advertisement of products through exposing trading partners to product related information. Although our result suggests that the effect size of exposure from the service provider's issued coupons is higher than that from the coupon trading, the total consumer generated exposure effect can easily surpass the amount produced by the service provider given a large consumer base. Hence, such 'voluntary advertising' among consumers can efficiently promote products and improve redemption rates.

On the other hand, some caution needs to be taken when implementing coupon trading. The result of the social exposure effect of coupon trading on coupon redemption is robust and consistent. However, we find that the positive effect can diminish if certain threshold is crossed. Coupon service providers may need to adjust consumers' receipt of trade requests from time to time in order to avoid the satiation in the social exposure effect of coupon trading. This can also avoid consumers perceiving an overwhelming number of trading requests as some kind of spam. In addition, the positive effect of coupon trading on coupon redemption due to consumer-induced exposure towards product related information appears to diminish in the long term. To keep a high level of effect, fresh stimuli of such social exposure is necessary. This requires coupon service providers to find the subtle balance between too much coupon trading and not enough coupon trading. Of course, to enjoy the social exposure effect of coupon trading, managers and marketers will first have to incur cost on building and maintaining trading mechanisms. The cost may include establishing dedicated cyber space and the continuous expansion and maintenance of servers. In some cases, such expense can be non-negligible. One eclectic way to approach such concern would be to organize coupon trading periodically as special events instead of a regular routine. Nevertheless, with the development of information technology, we are sure to witness a further decrease in hardware cost and a continuous increase in cost efficiency of equipment required for establishing coupon trading. We believe that regular coupon trading can be a viable and useful tool to improve online coupon service providers' business models.

3.5.3 Limitation

Although our paper offers important contribution to the existing literature, it also has some limitations. Though we have comprehensive consumers' behaviors, their socioeconomic information is not available to us. Such information would certainly extend our work. Besides, conversation logs during coupon trading can be very valuable to further improve our work. Combining empirical analysis with methods such as text mining can explore new research opportunities on coupon trading. In addition, we admit that our work might be finer grinded by building the model on shorter time intervals such as weeks or days given faster computational speed and higher memory capacity. For future research, replications with a finer time grid can be conducted to compare the results and to offer additional insight on related topics for both the academia and the industry.

3.5.4 Conclusion

In conclusion, coupon trading is a plausible business practice. The social exposure effect of coupon trading can increase coupon redemption probability. And most importantly, such effect is induced among consumers themselves rather than pushed by the service providers. We hope our work provides the academia and the industry with fresh insights on the coupon practice. We wish our work would encourage further research effort on coupon trading and related topics.

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4 Two Sides of the Same Coin: The Effect of Virtual Currency on User Behavior

Abstract

Virtual currency has now been widely adopted across online platforms to facilitate platform users' behaviors, to enhance their on-platform experience and to incentivize engagement. In this paper, we measure the effect of virtual currency on platform users' behaviors. We build this work on the self-sufficiency theory in the literature stream of money psychology. We apply our analysis on a longitudinal dataset from a Swiss online social gaming/shopping platform over a time span of 47 weeks. Our results suggest that virtual currency enhances platform users' individual behaviors, but lowers interaction among them. This study extends existing money psychology literature to virtual currency, offering important implication to researchers and practitioners.

Keywords: virtual currency, money, money psychology, self-sufficiency, fixed effects, Poisson regression

4.1 Introduction

For many people, they live two lives, one offline and another online. An indispensable part of the offline life for most of us is money. We use money to measure the values of various objects and services; we use money to pay for them; and we use money to store the value of assets for precaution. In recent years, we have witnessed the momentum in the shift of the emphasis from the offline world to the online world. The innovation in IT brings the experience of the offline life and that of the online life closer than ever. To facilitate people's experience in the online environment and lift platform users' engagement, virtual currency was introduced and popularized among online platforms over the past few years (Castronova, 2014). For example, on platforms such as the World of Warcraft, Amazon and QQ, virtual currency is introduced to make trades and purchases more convenient and to provide liquidity in the markets among their users in hope for an increased user involvement.

Virtual currency fulfills similar functions that money does in real world. It closely resembles money and plausibly acts as money under many circumstances though it may not function as well as money in certain aspects (Castronova, 2014). The belief that virtual currency can alter people's behaviors may be rooted in the power of money. Money is thought to be a driving force in people's behaviors. Recent research on money suggests that money has the power to motivate human beings due to its instrumentality (Lea & Webley, 2006). This is because that Money brings people a state of self-sufficiency, which induces people to exert more effort in personal goal attaining (Vohs, Mead, & Goode, 2006). However, while leading to a higher effort level in human beings' behavior, the self-sufficiency induced by money can also lead to estrangement at the same time (Vohs, Mead, & Goode, 2006). The desire for independence, personal control and autonomy resulted from self-sufficiency leads a preference less reliance and involvement among people, thus creating a longer interpersonal distance. Therefore, the question remains unanswered is whether virtual currency, as a close resemblance to money, properly incentivizes people. Or does it alienate people just as money also does? Virtual currency has now been widely adopted across online platforms to facilitate users' behaviors, to enhance their on-platform experience and to incentivize engagement. Unlike the time when "*virtual currency*" was still a buzzword, nowadays people are already used to it as a matter of course. Hence, given the fact that virtual currency has almost become a standard and indispensable part in the online environment, it is of vital importance to examine the effect it has on people's behaviors. Yet, empirical research on the effect of virtual currency is scarce, if not non-existing. In this study, we examine the effect of virtual currency on platform users' behaviors based on theories of money and money psychology. By doing so, we provide critical insights to marketers, platform operators and Internet practitioners. Today's online platforms value their users' engagement and the interaction among platform them more than anytime in the history because platforms' business models and financial successes are often built on that. Thus understanding the effect of virtual currency on user behaviors and user interactions can greatly improve platforms' operations and help them use virtual currency more wisely and less blindly.

Our empirical analyses are based on a longitudinal dataset from a Swiss online social gaming/shopping platform. Unlike most online platforms or games, virtual currency was not implemented as a basic element when this platform started its operation. The platform launched its own virtual currency about one year and half later. This unique feature is critical for our analyses because it offers us with the opportunity to investigate how users' behaviors are altered by virtual currency. Our longitudinal dataset consists of 16,962 platform users over a length of 47 weeks in 2013. Methodologically, we employ fixed effects Poisson (FEP) estimator (Wooldridge, 1999) to infer robust results (random effects models are also estimated for reference). We find that virtual currency does incentivize users' individual behaviors. But at the same time, we also find evidence that virtual currency diminishes communal motivations. Overall, our findings suggest that virtual currency, similar to money, encourages individualism and diminishes dependency and reliance, which can lead to a “play alone, work alone” mentality.

Our work has theoretical and practical relevance because it offers important contribution to both the academia and the industry. We extend previous literature on money psychology to the context of virtual currency. Such extension is very important for the relatively under-researched topic of virtual currency against the background of the high penetration of virtual currency in our lives. It also makes a critical contribution in bridging researches on money and researches on virtual currency given the ever-blurring boundary of the online and the offline world. We offer vital implications for practitioners on the usage of virtual currency. Though individual behaviors can be boosted by virtual currency, online platforms shall also keep an eye on its effect on the deteriorating interaction among platform users. Our results suggest that practitioners shall not over-optimistically believe in the incentivizing power of virtual currency. They need to carefully evaluate the negative effect of virtual currency on the interaction among platform users and take proper measures to compensate such side effect.

This paper is organized as follows: in the next section, we discuss the related literatures and the theoretical framework. Introduction on the dataset, the modeling strategy then follows. We present the results on the analyses and conclude the paper with implications.

4.2 Related Literatures and Theoretical Framework

To investigate virtual currency’s effect on platform users’ behaviors, we build our theoretical foundation of this study mainly on the literature of money psychology. As we argued earlier, virtual currency plausibly functions as money in cyber space. Thus, it is natural to extend theories on money to virtual currency.

4.2.1 Money and Money Psychology

This study is mainly grounded in the recent research development of money psychology. We borrow theories on money due to the similarity between virtual currency and money. Money is the set of assets in an economy that people regularly use to buy goods and services from other people (Mankiw, 2014). Money in any economy serves three functions: it is a medium of exchange, a unit of account and a store of value (Mishkin, 2007):

- Medium of exchange: as a medium of exchange, money, usually in the form of currency or checks, is used to pay for goods and services. The use of money as a medium of exchange promotes economic efficiency by minimizing the time spent in exchanging goods and services.
- Unit of account: as a unit of account, money is used to measure value in the economy. The use of money as a unit of account reduces transaction costs in an economy by reducing the number of prices that need to be considered. The benefit of such function grows as the economy becomes more complex.
- Store of value: as a store of value, money functions as a repository of purchasing power over time. Although many other assets have advantages over money as a store of value, money remains the most liquid asset among all in the sense that it is the easiest and fastest assets that can be converted into a medium of exchange since money itself is a medium of exchange.

Most money exists in the form of fiat money today compared to commodity money or commodity-backed money. While commodity money such as gold carry intrinsic value in itself, commodity-backed money and fiat money are not intrinsically valuable. The commodity-backed money is acknowledged as an item represents the underlying commodity.

The fiat money is established as a currency decreed by governments as legal tender. Both forms haven been universally accepted along human history. For commodity money, it was accepted due to its intrinsic value. And for fiat money, it was accepted based on the decree from government that the currency is a legal tender to pay any debts.

Money has been predominantly studied in a systematic way within the discipline of economics. For economists, such as Keynes, people demand money due to three motives, namely the transactions motive, the precautionary motive and the speculative motive (Keynes, 2006). This is rooted in the functions that money serves. As a medium of exchange, a unit of account and a store of value, people can use money to make purchases, to store wealth and to prepare for unexpected emergencies. However, recent development in other disciplines greatly enriched our understanding on money from different angles. In psychology for example, Lea and Webley developed two complimentary theories to argue how can money act as incentive and reinforcer (Lea & Webley, 2006). It was postulated that money incentivize and motivates people by functioning as a tool and as a drug. Being a tool of exchange, money provides strong incentive due to the goods and services it can buy. Being a drug, money intrudes on the normal functioning of the nervous system. While money's function as a tool has been well valued across human beings' history, its function on humans' nervous system were not well documented until recent research efforts in neurology. A special basal forebrain region was found to be the key node in translating money into motivational forces (Pessiglione, et al., 2007). However, as the old saying goes, every coin has two sides. That is all too accurate on money, literally or metaphorically. Vohs et al. (2006) proposed the self-sufficiency theory as an encapsulation of the work by Lea & Webley (2006) to further extend the explanation for the power of money. The self-sufficiency theory suggests that due to the instrumentality of money, it enables people to get things done independently rather than relying on others, thus inducing people entering a state of self-sufficiency. People under such state enjoy the feeling of personal control, autonomy and security because money to a large extent frees them from interdependence relationship. They believe that they can solve tasks without relying on others, thus exerting more efforts to achieve better personal performance. The lack of money on the contrary makes people feel ineffectual because they will be more heavily interdependent on social relationship, which explains why people craving for money. However, such emphasis on behaviors of one's own choosing without active involvement from others leads to diminishing dependency among people. They desire to be free from dependency and also prefer that others not depend on them. This creates a greater physical distance among people and builds the 'play alone, work alone' mentality.

4.2.2 Comparison between Money and Virtual Currency

Over the past decade, we have witnessed the growing popularity among social media such as games, services and businesses to introduce their own virtual currency. According to the definition proposed by the European Central Bank, a virtual currency is a type of unregulated, digital money, which is issued and usually controlled by its developers, used and accepted among the members of a specific virtual community (European Central Bank, 2012).

Virtual currency is launched in games and various social media platforms to motivate users to be more engaged (Castronova, 2014). Such practice is largely rooted in traditional economic understandings on money motive. However, whether virtual currency can fulfill this purpose remains unknown and has not be empirically tested. But more importantly, no research has ever examined virtual currency's effect on user interaction. If money creates larger distance among people, it is perfectly natural to speculate that virtual currency may very well be capable to do the same on online platform users. Since today's social media platforms dependents heavily on user interaction, such effect would be devastating. Therefore, it is imperative to investigate the effect of virtual currency. In order to do that, we inevitably have to compare virtual currency and money in the first place.

Virtual currency resembles money in that it fulfills similar functions in the virtual world as money does in the real world. However, due to the fact that virtual currency is not backed by legal entities, it may not be as effective as money in fulfilling certain function:

- Medium of exchange: same as money, virtual currencies can be used to pay for either virtual or real goods and services in cyber spaces. It is even thought as a better means of exchange than money from a pure efficiency point of view because it can avoid impositions that curtail exchange (Castronova, 2014).
- Unit of account: as a unit of account, virtual currency can be issued in fractions based on the numbering system of the platform. Since they can be applied on any numbering system, virtual currency is easily scalable. Thus, they can function perfectly as a unit of account.
- Store of value: to function as a store of value, virtual currencies shall ideally either possess intrinsic values that are not easily eroded or be legally backed by the issuing legal body that will be in stable operation for long enough. However, neither does virtual currency carries any intrinsic value, nor do online platforms possess legislative authority to declare virtual currency's legality. It therefore relies solely on platforms' reputation and prospect to make virtual currency a proper store of values. Yet, online platforms are far less stable compared to modern governments. Obviously, virtual currency can be store of value to some extent (i.e., as long as the issuing platforms still prosper in business). But they will not be as effective as money to carry out this function.

Though probably not being as effective as money in fulfilling all the basic functions as an instrument, virtual currency closely resembles money in the cyber world. The similarity between virtual currency and money thus seems to favor the widely adopted practice of using virtual currency as a motivation driver in online environment. Nevertheless, due to the similarity to money, it is also plausible to speculate that the self-sufficiency induced by money may also be triggered by virtual currency. Specifically, virtual currency, like money, may alienate people from their peers. It can result in grieve consequence since most online platforms usually rely heavily on user interaction as the backbone of their business models. If this is the case, then virtual currency can be a double-edge sword for online platforms in the sense that it incentivizes only individualism but diminishes interaction. The combination of the potentially positive and negative effect of virtual currency on people's behaviors leaves us with a big question mark on the validity of arbitrarily adopting virtual currency as an incentive scheme. This also underscores the importance of our study to both the academia and the industry.

4.3 Empirical Analysis

4.3.1 General Setting

This study collects data from a Swiss online social gaming and shopping platform founded at the end of 2011, which prefers to remain anonymous. The experience on the platform resembles an online Collecting/Trading Card Game (CCG/TCG). Users could collect cards, which stand for discount vouchers on various products, and could trade them with other users and accumulate discounts for product redemption. While product redemption and login were the most direct and intuitive measure of users' engagement on the platform, their social interaction on the platform primarily lay in trading activities. The gamification of the experience on the platform (i.e., trading cards) differentiated the platform from its competitors and earned it its niche position in the market. In a word, the platform depended primarily on users' engagement and interaction to build up its reputation among suppliers and to attract external investment. In early June 2013, the platform launched its own virtual currency. Platform users could use virtual currency to pay for additional discount on the products. Virtual currency could be collected through daily login as users were awarded with random cards including virtual currency upon daily login. They could also collect virtual currency by exchanging cards for virtual currency with others. Unlike most of the virtual currency schemes, which are usually implemented as part of the basic functions upon the launch of platforms, the platform in this study introduced its virtual currency when the operation was stable. Therefore, our data offers us with the unique opportunity to investigate the effect of virtual currency on platform users' behaviors.

Since our work is built upon theories related to money, we essentially assume that virtual currency resembles money. This is true in our case as the platform's virtual currency, same as other virtual currency, fulfilled the three major functions of money to a large extent: medium of exchange, unit of account and store of value. Specifically, virtual currency served as a medium of exchange because it could be used in trades among platform users, be used to exchange for additional discount on a product, and be used to exchange for additional chances to draw random cards. Since its launch, the percentage discount on a product (i.e., one unique card stands for 10% discount on a product) was also enlisted in the form of virtual currency. Therefore, virtual currency also served as a unit of account on the product value. Virtual currency stored value to some extent since it was backed by the platform, which saw no danger of immediate collapse at the time of the launch. Thus, virtual currency on the platform was indeed similar to money.

4.3.2 Data and Model

We build our empirical analyses on a longitudinal dataset collected from late January 2013 to late December 2013 over a total length of 47 weeks. The panel is unbalanced since different users joined the platform at different times. Users who had at least one login during the whole period of study are selected to form the sample. Within the period of study, the platform recorded 16,962 platform users who logged in for at least once, 1,315,899 logins, 711,256 trade proposals and 35,227 product redemptions. To test virtual currency's effect on platform users' behaviors, we examine three most important behaviors on the platform: product redemption, login and proposing trades. These three measures are chosen because they best fit the platform's business model. Moreover, they are fairly direct and intuitive in reflecting users' engagement and their interaction, thus inline with our target on testing the effect of virtual currency:

- Weekly product redemptions (*RediW*): The ultimate goal of platform users is to redeem products. Virtual currency, a flexible payment method (for additional discount) as the result of its instrumentality of being a medium of exchange, shall increase platform users' redemption incidences. Besides, if virtual currency induces self-sufficiency, then users would exert more efforts in attaining personal goals, which would also lead to a higher number of product redemption incidences as a result.
- Weekly login days (*LogDiW*): Login is a commonly recognized measures on engagement adopted by online games and various social media nowadays. Since virtual currency serves similar functions as money does, platform users would likely value it for its instrumentality, just as people demanding for money in real world. Virtual currency enabled them with autonomy in their activities on the platform, which would have been ineffectual if no virtual currency existed. Therefore, users would increase their login frequencies because that would give them a higher chance in obtaining more virtual currency. Login days rather than the number of logins are used because the random cards, which included virtual currency, were awarded to users upon daily login. In another word, users received random cards only upon their first login within a day. Multiple logins within a day did not necessarily increase the

chance to earn more virtual currency. Hence, the number of days in a week on which a platform user logged in is the more appropriate measure.

- Weekly trade proposals (*TrdPiW*): Interaction among platform users are vital to the success of various online platforms. Nevertheless, the self-sufficiency theory suggests that money induces a preference of less dependency and less involvement from others. If this also applies to virtual currency, it can lead to a decrease in trade proposals conditional on logins (i.e., lower trade proposals rate). The reason for this is that though virtual currency could arguably facilitate trading as a medium of exchange, trading activities required extensive interaction among trading partners, which is less preferred if self-sufficiency is induced. For example, as channels to collect cards for discount, login and using virtual currency for additional chances to draw random cards empowered users with higher personal control and autonomy compared to trading, which required more reliance, dependency and mutual involvement. Similarly, in obtaining virtual currency, for the same logic, platform users would prefer higher login frequencies to trading. In addition, with the emergence of demand for virtual currency, arguably more platform users would require virtual currency in return during trading, which might cause difficulty in matching mutual needs. All of these would result a much more significant increase in login rather than that in trade proposals. Consequently, with the introduction of virtual currency, platform users might play more often, but only by themselves rather than with others.

A simple graphic comparison of the three measures conditional on whether affected by virtual currency is shown in Figure 4.1-4.3. It is evident that the average weekly product redemptions and login days when users were exposed to virtual currency are obviously higher than those when users were not exposed to virtual currency. The drop if trade proposal rate is also evident from the graph.

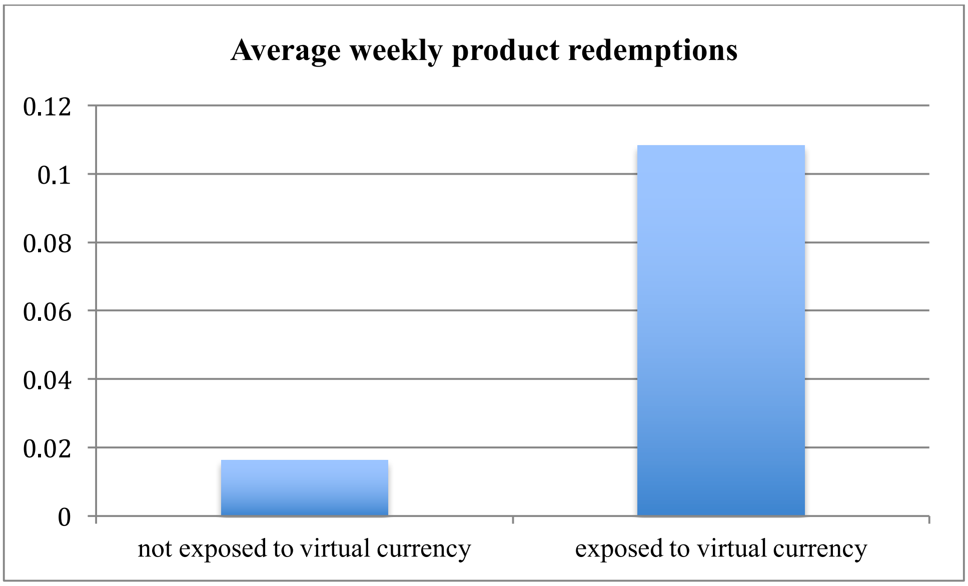

Figure 4.1 Comparison of average weekly product redemptions conditional on whether exposed to virtual currency

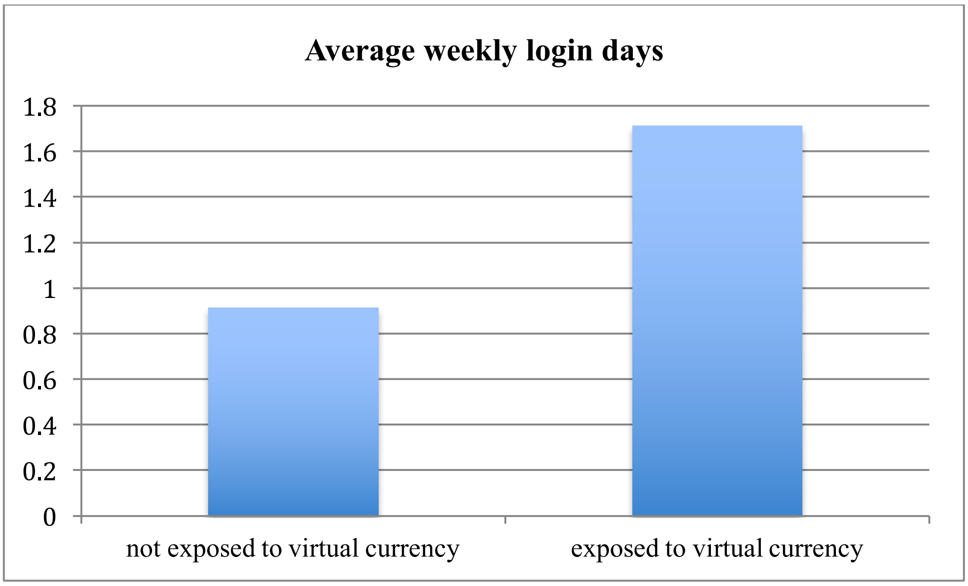

Figure 4.2 Comparison of average weekly login days conditional on whether exposed to virtual currency

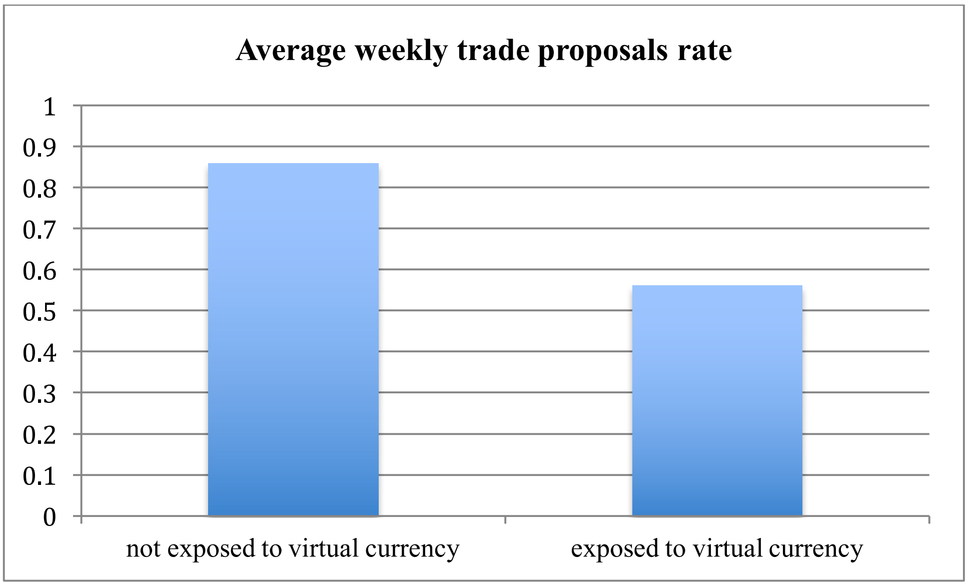

Figure 4.3 Comparison of average weekly trade proposal rate conditional on whether exposed to virtual currency

4.3.3 Empirical Model

We use a dummy variable *VC* to capture the effect of virtual currency on platform user behaviors. It is operationalized as 1 since users' first login after the launch of virtual currency and 0 before that. Note that in this setup, though the virtual currency was launched on a specific date, different users were potentially affected by it from different dates (or not exposed to it at all) (i.e., users started to be potentially influence by virtual currency only since their first login after the launch). As illustrated in Figure 4.4, though the event occurs at T=3, only user B was immediately exposed to virtual currency since he logged onto the platform in the same week after the launch. User A on the other hand was not immediately exposed to it since he had not yet logged in. User A's first login after the launch is at T=6. Therefore, the dummy variable turns to 1 only since T=6. User C joined the platform at T=8. Thus, *VC* is recorded as 1 only since T=8. User D, an existing user same as user A and user B, had no login record after the virtual currency was launched. Hence, for user D, *VC* is 0.

A:	0	0	0	0	0	1	1	1	1	1	1	1
B:	0	0	1	1	1	1	1	1	1	1	1	1
C:								1	1	1	1	1
D:	0	0	0	0	0	0	0	0	0	0	0	0
T	1	2	3	4	5	6	7	8	9	10	11	12

Figure 4.4 Operationalization of virtual currency dummy variable in the main analysis

Given the nature of our dependent variable, which is non-negative discretely distributed, it is a natural choice to estimate our regression equations using count models. Specifically, we use Poisson regression to model platform user i's product redemption behavior, login behavior and his trading behavior at time t and estimate the following models:

$$\text{Product redemptions: } E(RediW_{it}|\boldsymbol{x}_{it}, \phi_i) = \phi_i exp(\boldsymbol{x}'_{it}\boldsymbol{\beta})$$

$$\text{Login days: } E(LogDiW_{it}|\boldsymbol{x}_{it}, \phi_i) = \phi_i exp(\boldsymbol{x}'_{it}\boldsymbol{\beta})$$

$$\text{Trade proposal: } E(TrdPiW_{it}|\boldsymbol{x}_{it}, \phi_i) = \phi_i exp(\boldsymbol{x}'_{it}\boldsymbol{\beta} + \ln TLog_{it})$$

Where $\boldsymbol{x}_{it}$ is the vector of covariates:

t, t2: the quadratic function of time capturing a general polynomial trend in users' behaviors

LastLog: recency of the focal platform user's login (i.e., number of weeks since their last login)

PastLogW: the focal platform user's total past login weeks

PastTrdP: the focal platform user's total past trading activities (which includes both trades proposed and trades received)

PastSucTrd: the focal platform user's total past successful trades

PastRed: the focal platform user's total past product redemptions

PastSpending: the focal platform user's total past monetary spending

NPrd: the focal platform user's current holding of potentially redeemable products (i.e., number of product of which at least one card is in users' possession)

DPrd: the median of the percentage discount of the focal platform user's potentially redeemable products

UPLike: the number of products liked by the focal platform user (the platform offered the function for users to indicate the product they liked)

Advertising: Weekly advertising cost, controlling promotion and advertising effect

NumPrd: weekly number of product available on the platform

MedPrice: median product prices on the platform, controlling the general price level

And ϕ_i is the individual effects that enter the model multiplicatively. While the number of days in a week is the same for every user, the number of logins in a week varies across platform users. Therefore, we use the number of total logins in a week (*TLog*) of the focal user's as the exposure variable in the trade model to model users' trade proposals in a week conditional on the number of logins (i.e., trade proposals per login or trade proposal rate).

The time trend variables, various platform and user variables over multiple observations along the study period, and together with the individual effect essentially model how users would have behaved if they were not exposed to the launch of virtual currency. The variable *VC* thus identifies the effect of virtual currency on platform users' various behaviors. In Table 4.1, we report the summary statistics of the variables. Before proceeding to the estimation issues, we spend a few lines giving an overview of the summary statistics.

Average consumers were not heavily addicted to the platform according to the login variable and the login recency variable. However, the consumer base seemed stable as the on average platform users visited the platform over 21 weeks. This is also suggested by their trading variables. Though on average individuals did not particularly trades on a frequent base, their cumulative trading records were relatively higher. Average successful trades suggest that the success rate was not particularly high. On average, it seems that platform users were not particularly fond of the products on the platform. They did not possess many potentially redeemable products. And they had relatively low discount on those potentially redeemable products. Their redemption incidence was very rare. Monetary spending by platform users was not high either. The spending on advertising seemed sufficient and product availability was abundant. The general product price level on platform was moderate. The variables are grand mean centered whenever appropriate.

Table 4.1 Summary statistics and definitions of variables

Variable	Mean	Std. Dev.
RediW	0.04894	0.63428
LogDiW	1.19582	2.26790
TrdPiW	0.98813	10.96842
PastLogW	21.23969	21.33791
LastLog	11.69991	12.40689
PastTrd (in hundred)	2.73906	7.49613
PastSucTrd (in hundred)	0 .42453	1.21650
PastRed	2.39790	9.21249
PastSpending (in hundred)	0.53439	2.43727
NPrd	6.09715	10.01371
DPrd (with 1 corresponding to 100% discount)	0.53240	0.64114
UPLike	0.22073	0.86383
Advertising (in thousand)	2.44930	2.40488
NumPrd	56.14923	17.97417
MedPrice (in hundred)	1.35158	0 .29767

Since the outcome variables (i.e., users' product redemptions, logins and trade proposals) are non-negative integers, linear regression can lead to significant deficiency due to the ignorance of the restricted support for the outcome variables (Cameron & Trivedi, 2013). Standard Poisson regression assumes that the data is equidispersed. However, this assumption is rarely met in practice. In social science, data commonly exhibits overdispersion, which violates the underlying assumption of the standard Poisson regression. Such violation results in incorrect standard errors. Therefore, instead of standard Poisson regression, the fixed effects Poisson regression with robust standard errors is used. The resulting fixed effects Poisson (FEP) estimator is free from distribution assumptions and is fully robust to issues such as serial correlation (Wooldridge, 1999). Since the fixed effects estimator is generally more robust than the random effects estimator in Poisson regression, we base our interpretation on the results from the fixed effects models. However, we also estimate the random effects models where the individual effect ϕ_i is assumed to follow gamma distribution with mean one and variance α. The effect of virtual currency is largely coherent between the fixed effects models and the random effects models. The estimation is conducted in Stata 13.

4.4 Results

In this section, we report the estimation results of the models. All estimation results are summarized in Table 4.2. AIC of the fixed effects models (product redemption model: 134183.4, login model: 1060763, trade proposal model: 944586.2) compared to that of the pooled models (product redemption model: 164767.6, login model: 1195157, trade proposal rate model: 1029909) indicates that models with individual effects indeed perform better. It shall be noted that users who have only one observation or those whose outcome variables are always zero are left out when estimating the fixed effects models. The number of observations is also reported in Table 4.2. As we introduced earlier, users' product redemption and trading were not particularly frequent on the platform. This explains the fairly large difference in the number of observations between the fixed effects models and random effect models. It is important to note that the reduced sample size in the fixed effects models is unrelated to truncation or selection. Those observations are properly dropped because they are uninformative for estimating the parameters in the fixed effects models. In addition, the observations in the trade proposal model are lower because only observations with weekly total logins more than zero are used for the estimation (the exposure variable has to be strictly positive).

Table 4.2 Results of the main analysis

	Product Redemption				Login Days				Trade Proposal per Login			
	Fixed Effects		Random Effects		Fixed Effects		Random Effects		Fixed Effects		Random Effects	
t	0.023212	(0.006875) ***	-0.021380	(0.004077) ***	-0.058309	(0.001472) ***	-0.052372	(0.001074) ***	-0.027285	(0.006047) ***	-0.023935	(0.003719) ***
t2	-0.002509	(0.000178) ***	-0.002201	(0.000216) ***	0.000483	(0.000019) ***	0.000490	(0.000018) ***	-0.000685	(0.000126) ***	-0.000668	(0.000127) ***
VC	0.464845	(0.069264) ***	0.581562	(0.089067) ***	0.408233	(0.009665) ***	0.413274	(0.009632) ***	-0.320793	(0.052437) ***	-0.321543	(0.051902) ***
PastLogW	-0.024126	(0.006949) ***	0.022346	(0.003780) ***	0.025909	(0.001574) ***	0.019887	(0.000982) ***	0.002819	(0.007069)	-0.000742	(0.004237)
LastLog	-0.053404	(0.013306) ***	-0.091867	(0.048631) *	-0.151236	(0.002928) ***	-0.167188	(0.005251) ***	0.010699	(0.003595) ***	0.005420	(0.003867)
PastTrd	-0.002926	(0.009838)	0.014336	(0.013753)	-0.000495	(0.002197)	-0.001158	(0.002020)	-0.020133	(0.006417) ***	-0.019142	(0.006316) ***
PastSucTrd	0.017919	(0.048846)	-0.035747	(0.041977)	0.015342	(0.009779)	0.022687	(0.009907) **	0.078462	(0.026408) ***	0.076215	(0.026489) ***
PastRed	-0.006461	(0.002598) **	-0.007855	(0.002857) ***	-0.001765	(0.000627) ***	-0.002109	(0.000675) ***	0.002027	(0.001706)	0.001789	(0.001749)
PastSpending	-0.068519	(0.025960) ***	-0.026886	(0.022492)	0.005044	(0.003635)	0.002405	(0.003323)	-0.016483	(0.013127)	-0.014204	(0.012627)
NPrd	0.042700	(0.003360) ***	0.042257	(0.003594) ***	0.031330	(0.000497) ***	0.032215	(0.000576) ***	-0.003133	(0.001978)	-0.002979	(0.001970)
DPrd	0.053752	(0.045146)	0.100282	(0.059227) *	0.013055	(0.005837) **	0.016375	(0.005853) ***	0.182969	(0.026778) ***	0.185349	(0.026047) ***
UPLike	0.071600	(0.018098) ***	0.083180	(0.024109) ***	0.034158	(0.003835) ***	0.035031	(0.003833) ***	0.041282	(0.019346) **	0.041599	(0.019550) **
Advertising	-0.014662	(0.009523)	-0.018682	(0.009725) *	0.008856	(0.000711) ***	0.009398	(0.000726) ***	-0.002281	(0.005480)	-0.002281	(0.005510)
NumPrd	-0.012767	(0.001752) ***	-0.013144	(0.001804) ***	-0.003136	(0.000130) ***	-0.003193	(0.000133) ***	0.005566	(0.000871) ***	0.005500	(0.000877) ***
MedPrice	-0.585866	(0.087986) ***	-0.650551	(0.110402) ***	-0.324347	(0.006651) ***	-0.333555	(0.007076) ***	-0.074324	(0.057605)	-0.073718	(0.057483)
Intercept			-4.976660	(0.425545) ***			-2.294909	(0.042852) ***			-0.968395	(0.068993) ***
alpha			7.662126	(12.220760)			0.936835	(0.339335)			3.376585	(2.608207)
number of obs	122028		719798		719791		719798		168900		203491	

*, ** and *** indicate the significance levels are at 10%, 5% and 1%

For the product redemption model, the result shows that virtual currency indeed increased users' redemption numbers (*VC*: 0.464845 (0.069264)). This suggests that virtual currency, as an incentivizing force and as an instrument of payment, facilitated platform users in attaining their goal of product redemption. With the launch of virtual currency, their redemption incidents increased by more than 46% on average. For the login equation, the result shows that virtual currency also increased platform users' login frequencies (*VC*: 0.4082326 (0.009665)). This suggests that the demand for virtual currency drives users to log onto the platform significantly more often. The number of days on which users logged in increased by more than 40% on average. As we have expected, virtual currency led to a drop in trade proposals by more than 32% (*VC*: -0.320793 (0.052437)) on average. This corroborates our speculation that virtual currency undermined interaction among users. The finding on the effect of virtual currency echo previous research on money and testifies that, same as money, virtual currency incentivizes users, but only in terms of individualism.

The other variables also show interesting findings. The time trend across the models indicates that user activities were dropping along the period of the time in general. The longer time since users' previous login (*LastLog*), the less active users would become in product redemption and login. Users' past login weeks (*PastLogW*) suggests that users who stayed longer on the platform would tend to login at a higher frequency. But they would have fewer product redemptions. This somehow passive behavior may be rooted in the fact that the engagement level of platform users was fading in general and the login behavior was a result of mere habit. Users who were involved in more trading activities in the past (*PastTrd*) would be less active in proposing trades presumably due to the fade in their interest in the gaming mechanism. However, successful trading experience (*PastSucTrd*) seemed to compensate the fading interest and increased users' trade proposals. Users' larger past product redemption amount (*PastRed*) would lower their product redemption and login frequency. This is probably because that with the increase in the accumulated redemption incidents, users' feeling of freshness and motivation diminished. Users' past monetary spending (*PastSpending*) lowered their product redemption frequency. In most social shopping or gaming, people prefer to play or get things for free. Increasing spending would therefore limit their further active engagement. The variables on users past behaviors underscore the importance for online platforms to stimulates users' interest and motivation, a point that we will discuss again in next section. Not surprisingly, with the increase in the potentially redeemable products users had (*NPrd*), the discount they enjoyed (*DPrd*) and the number of products liked (*UPLike*), users generally became more active.

As to the platform level variables, we find that advertising (*Advertising*) was positively associated with users' login only. This indicates that advertising presumably can attract people to the platform, but not necessarily make them extra active on the platform. Increasing the numbers of products on the platform (*NumPrd*) seemed to correlate to lower product redemption. It is likely because that the increase in product numbers increased users' mental burden in strategically collecting their vouchers, which reduced their redemption incidents. Users seem not to favor such expansion as their login frequency also dropped. The positive association between the number of product and users' trade proposal rate is probably because users on average would have more resources to make trades with more products on the platform. The general price level (*MedPrice*) is negatively associated with users' product redemptions and login frequency, indicating the business model should be based on bargains rather than expensive products.

4.5 Robust check

In the main analysis we operationalize the variable of virtual currency in the way that the effect of virtual currency started since users' first login after the launch of the virtual currency. This is plausible as users were only affected by the virtual currency when they were exposed to the environment in which the virtual currency was implemented. That started since the first time when users logged on to the platform after the launch of the virtual currency. However, one can argue that some users might have learnt the launch from other channels and consequently decided to leave the platform for good before they experience the updated platform with virtual currency. We would like to state that this is fairly unlikely. Virtual currency has existed in games and social media platforms for decades. Indeed, as Castronova (2014) suggested, players would probably be surprised to find a virtual world without a virtual currency. Therefore, it is very difficult to imagine that on a social shopping/gaming platform, such as the one in this study, which resembles a TCG/CCG game, users would not log onto the platform for even once simply due to the launch of virtual currency. Yet, to ensure the robustness of this study, we conduct a robust check to further validate our results. The argument of users might have learnt the launch of virtual currency and accordingly decided to leave the platform implies that those users were also exposed to the virtual currency. Based on this logic, we push the limit of such logic even further and impose an assumption that every user in the sample was exposed to the virtual currency at the earliest possible time, which is the week of the launch. This operationalization is illustrated in Figure 4.5 with the event occurs at T=3. Only now, different from that in the main analysis, user B is not the only user who is immediately exposed to virtual currency. User A and user D are also exposed to virtual currency at T=3 as well because we assume that every one

A:	0	0	1	1	1	1	1	1	1	1	1	1
B:	0	0	1	1	1	1	1	1	1	1	1	1
C:								1	1	1	1	1
D:	0	0	1	1	1	1	1	1	1	1	1	1
T	1	2	3	4	5	6	7	8	9	10	11	12

Figure 4.5 Operationalization of virtual currency dummy variable in the robust check

learnt the event somehow from other channels. User C is still exposed at T=8 since that is the time he joins the platform. We would like to emphasize that this is a very strong assumption since it essentially assumes that within the same week of the launch, every user, even without logging onto the platform, learnt the event. The imposition of such a strong assumption may seem implausible since if users did not learn the event within the launching week, such operationalization would dilute the effect of virtual currency conditional on the general time trend and platform variables. This would essentially lead to the most conservative results on the effect of virtual currency. Therefore, for the sack of robustness, we shall only use the results of this extreme setup as a test on the lower bound of virtual currency's effect.

The results of the robust check are shown in Table 4.3. We would like to note that the results on the effect of virtual currency under this setup are consistent in signs and significance compared to those in the main analysis. Since this robust check serves as a test on the lower bound of the effect of virtual currency, the coherent in the signs and significance again shows the evident effect of virtual currency on platform users' behaviors. As expected, the outcome is indeed more conservation compared to the results from the main analysis. For the product redemption model, the effect of virtual currency on users' product redemptions shrinks by about half (*VC*: 0.221995 (0.065682)). This suggests that virtual currency, under the assumption we made in the robust check, increased users' redemption incidents by more than 22%. For the login equation, the shrinkage is even larger (*VC*: 0.135274 (0.007056)). This suggests that virtual currency, under the assumption we made in the robust check, increased users' redemption incidents by more than 13%. Since the trade proposal model only includes observations where total logins in a week is strictly positive, the result from the robust check coincides with that from the main analysis (*VC*: -0.320793 (0.052437)), indicating a more than 32% drop in users' trade proposals. A graphic comparison between the results from the main analysis and the robust check is presented in Figure 4.6.

Table 4.3 Results of the robust check

	Product Redemption						Login Days						Trade Proposal per Login					
	Fixed Effects			Random Effects			Fixed Effects			Random Effects			Fixed Effects			Random Effects		
t	0.033519	(0.007105)	***	-0.008976	(0.004630)	*	-0.050003	(0.001519)	***	-0.043483	(0.001128)	***	-0.027285	(0.006047)	***	-0.023935	0.003719	***
t2	-0.002778	(0.000178)	***	-0.002586	(0.000191)	***	0.000302	(0.000018)	***	0.000306	(0.000017)	***	-0.000685	(0.000126)	***	-0.000668	0.000127	***
VC	0.221995	(0.065682)	***	0.229394	(0.065227)	***	0.135274	(0.007056)	***	0.135001	(0.007035)	***	-0.320793	(0.052437)	***	-0.321543	0.051902	***
PastLogW	-0.025829	(0.007080)	***	0.022547	(0.003603)	***	0.026723	(0.001604)	***	0.020236	(0.001020)	***	0.002819	(0.007069)		-0.000742	0.004237	
LastLog	-0.061262	(0.013282)	***	-0.105761	(0.052507)	**	-0.160203	(0.002916)	***	-0.176624	(0.005273)	***	0.010699	(0.003595)	***	0.005420	0.003867	
PastTrd	-0.002715	(0.009905)		0.014525	(0.013764)		0.000065	(0.002191)		-0.000724	(0.002020)		-0.020133	(0.006417)	***	-0.019142	0.006316	***
PastSucTrd	0.017812	(0.048951)		-0.035847	(0.042223)		0.014036	(0.009736)		0.021669	(0.009894)	**	0.078462	(0.026408)	***	0.076215	0.026489	***
PastRed	-0.006459	(0.002606)	**	-0.007875	(0.002877)	***	-0.001863	(0.000632)	***	-0.002191	(0.000679)	***	0.002027	(0.001706)		0.001789	0.001749	
PastSpending	-0.068327	(0.026009)	***	-0.026964	(0.022430)		0.005167	(0.003604)		0.002488	(0.003299)		-0.016483	(0.013127)		-0.014204	0.012627	
NPrd	0.042449	(0.003362)	***	0.041818	(0.003583)	***	0.031336	(0.000498)	***	0.032246	(0.000581)	***	-0.003133	(0.001978)		-0.002979	0.001970	
DPrd	0.054538	(0.045285)		0.101667	(0.059563)	*	0.011172	(0.005777)	*	0.014298	(0.005785)	**	0.182969	(0.026778)	***	0.185349	0.026047	***
UPLike	0.072187	(0.018200)	***	0.083946	(0.024277)	***	0.036134	(0.003951)	***	0.036994	(0.003949)	***	0.041282	(0.019346)	**	0.041599	0.019550	**
Advertising	-0.005833	(0.009625)		-0.006634	(0.010282)		0.017894	(0.000669)	***	0.018606	(0.000697)	***	-0.002281	(0.005480)		-0.002281	0.005510	
NumPrd	-0.012115	(0.001729)	***	-0.012216	(0.001763)	***	-0.002016	(0.000126)	***	-0.002048	(0.000128)	***	0.005566	(0.000871)	***	0.005500	0.000877	***
MedPrice	-0.470118	(0.086386)	***	-0.483999	(0.096065)	***	-0.218858	(0.006574)	***	-0.226112	(0.006854)	***	-0.074324	(0.057605)		-0.073718	0.057483	
Intercept				-4.832548	(0.433520)	***				-2.183225	(0.043558)	***				-0.968395	0.068993	***
alpha				7.802984	(12.433560)					0.942529	(0.340867)					3.376585	(2.608207)	
number of obs	122028			719798			719791			719798			168900			203491		

*, ** and *** indicate the significance levels are at 10%, 5% and 1%

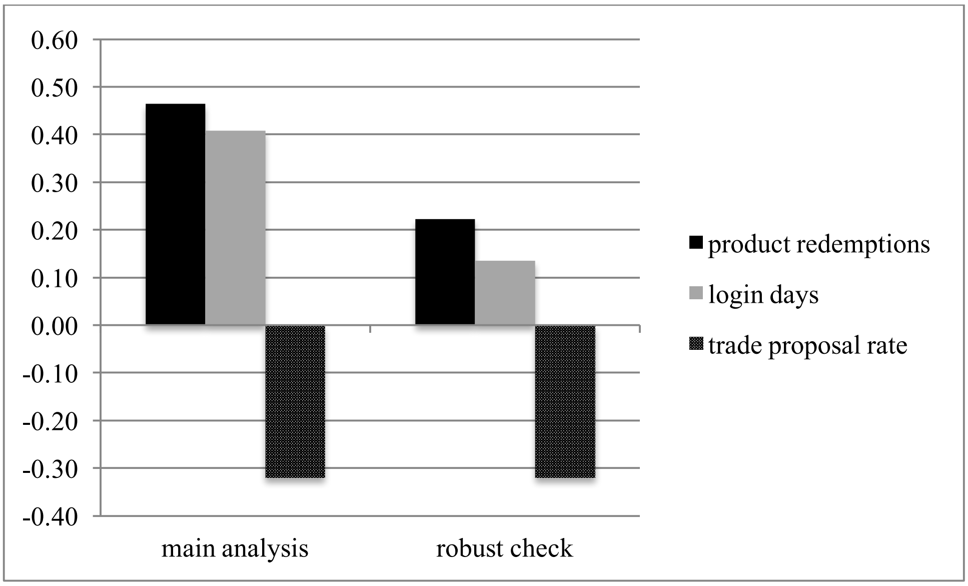

Figure 4.6 Comparison of the effect of virtual currency between the main analysis and the robust check

4.6 Conclusions and Implication

In this paper, we investigate the effect of virtual currency on a unique dataset of 16,962 users from a Swiss online social gaming/shopping platform. Through our empirical analyses using fixed effects Poisson regression, we find that virtual currency can indeed boost platform users' behaviors. However, it lowers interaction among platform users at the same time. This suggests that the self-sufficiency induced by money also applies to virtual currency. The findings in this paper offer several important implications to both theories and practices.

4.6.1 Implication for theory

The most important theoretical implication is that we extend money psychology to virtual currency. Though a popular phenomenon, the amount of research on virtual currency is limited compared to that on money. However, with the fast increasing in total value of virtual currency over the world, it deserves more research attention. Virtual currency has been argued as a close resemblance to money mainly due to its instrumentality. Our results suggest that in addition to the instrumentality, virtual currency seems to have similar effect on platform users' behaviors as money does on people. This has important implications because it brings virtual currency and money even closer. Since virtual currency is a relatively new phenomenon and lacks general theoretical framework, the closeness between virtual currency and money indicates promising researches opportunities in theory building related to virtual currency by utilizing the fruitful research outcomes on money. The bridging between the two can extend our current understanding on virtual currency and address unsolved issues.

The results of this work also provide implications to the literature of customer engagement, especially among virtual communities. Though widely used by practitioners, the concept of customer engagement did not draw much research attention in marketing literature except for some pioneering work (Algesheimer, Dholakia, & Hermann, 2005). Since that, however, we have witnessed significant development in this stream of literature (Marketing Science Institue, 2010). Due to the prevalence of virtual world in our lives, specific research attention has been paid on customer engagement in virtual communities (Brodie, Ilic, Juric, & Hollebeek, 2013). However, as an important part of virtual world, virtual currency's potential effect on engagement has been overlooked. From the results of this study, we see the opportunity for new addition and extension to the customer engagement literature. According to Vivek, Beatty, and Morgan (2012) customer engagement refers to the intensity of an individual's participation and connection with the organization's offerings and activities initiated by either the customer or the organization. And users' interactive experience has been argued as an important aspect of customer engagement (Van Doorn, et al., 2010). The results of this study suggest that while virtual currency can indeed encourage users to increase the intensity of individual participation on platforms, it also limits users' interactive experiences. Therefore, the effect of virtual currency on engagement is significant but mixed, potentially an addition and extension to Hennig-Thurau et al.'s (2004) eight-factor theory on what motives engagement with online communities. There has been very limited research on the effect of virtual currencies on user engagement (Wang & Mainwaring, 2010). And no empirical analysis on this topic has been recorded in the existing literature. Hence, our work broadens the customer engagement literature by showing the necessity to incorporate virtual currencies in this stream of literature.

4.6.2 Implication for practice

Our findings are also relevant for online platforms and communities. User life cycle on social gaming and retailing platform are rather short. According the report from Flurry, the 90-day retention rate of social games and retailing apps were just 29% and 33% (FLURRY, 2012). The results of our analyses also find similar phenomenon in the sense that users inevitably become less and less active due to the fade in their motivation and the feeling of freshness. As a result, new contents or services have to been carried out on a frequent base to satisfy users' needs and to keep them interested. However, such strategy may not always work. First, it will require platform operators to push forward new contents with acceptable quality on a frequent base, which simply may not be possible due to resource limitations. Second, assuming platform operators have the resources to push forward new contents on a frequent base. This would usually suggest that users probably have to spending more to fully experience all contents due to the fact that online platforms' business models nowadays are usually built on microtransaction. This can lead to dissatisfaction among users and may backfire. Third, even if most of the new contents are free of charge, the fasting growing contents on the platform will very likely lead to an increase in the complexity, which is not very friendly to new users or users with less experience. Therefore, an alternative way may be needed to incentivize users. The answer to this question for many practitioners, based on the trend among online platforms over the past few years, seems to use virtual currency. However, the underlying reasoning for many applications may be just vaguely based on traditional economic sense that virtual currency would make the market of exchange more liquid. Our results show that without fully understanding the effect of virtual currency, the implementation can lead to unsatisfactory result.

The results of this study suggest that virtual currency can be used to incentivize users' certain behaviors. It can be used as an effective way to keep users on the platform and increase their visit frequencies. It will induce users to exert more efforts in attaining personal goals and partially facilitate their payment routines. All of these merits brought by virtual currency are very help for online platforms to build up user bases and to keep users engaged in achieving goals on the platform. This in turn enables platforms to promote their reputation and attract investments. Yet, it shall also be noted that virtual currency should be used with caution. Our findings show that, like money, virtual currency also leads to lowered interaction among platform users. The preference of personal control and autonomy with less reliance and involvement from others can be detrimental to online platforms whose successes rely heavily on user interaction. Indeed, virtual currency can motivate users to stay on the platform and to exert more efforts to achieve personal target. Yet, they will tend to achieve that by their own with less and less involvement of others. In the end, the interactive experience will be minimum. For online platforms that heavily depend on user interaction as the core of their business model, a growing users base with low user interaction essentially creates an illusionary prosperity. If platforms are filled with users who *'play alone and work alone'*, either the platforms will have to change their business models to reduce dependency on user interaction, or they will lose competitiveness in the market.

Online platforms want to keep users on the platforms. Virtual currency's incentivizing power can deliver that. But online platforms do not want users to shy away from interaction. Unfortunately, that is something virtual currency can also deliver. As money is formidable in human society, virtual currency is a powerful but double-edged sword in the hands of Internet business practitioners. We recommend carefulness in its usage. Platforms shall evaluate their business model thoroughly before adopting virtual currency. We suggest practitioners to carefully device their virtual currency or to take necessarily measures to minimize or compensate the potential side effect of virtual currency on user interaction.

4.6.3 Limitations

Although our paper offers important contribution to the existing literature, it also has certain limitations. In this study, we identify the causal relationship between virtual currency and users' behaviors by controlling the baseline time trend, user and platform level variables and unobserved heterogeneity on longitudinal dataset. An additional robust check is adopted to ensure the validity of the results. Since this research is conducted in a retrospective way in the sense that virtual currency was already launched on the platform at the point of data collection, there was no opportunity for us to design a randomized experiment. To improve generalization, future studies can conduct randomized experiment and compare the results with this study. Moreover, future study can conduct studies for longer periods and compare the results with researches on money. In this way, long-term effect pattern of virtual currency can be investigated, potentially offering more insights in related topics. We hope that this work will encourage more research efforts on virtual currency and its effect on people's behaviors.

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Curriculum Vitae

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